# Narrative Finance: A Primer

## Theoretical Foundations, Measurement Methods, and Practical Applications for Finance Research

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**Abstract**

This primer provides a comprehensive introduction to narrative finance, an emerging field that examines how stories, beliefs, and shared narratives influence financial markets and economic outcomes. We address three key gaps in the literature: (1) the lack of a formal definition of financial narratives, (2) the absence of a systematic taxonomy, and (3) the need for a rigorous measurement framework. We propose a five-component definition of financial narratives—encompassing story structure, collective emergence, action-orientation, temporal logic, and economic relevance—and develop an eight-category taxonomy covering market-focused and context-focused narrative types. Our methodology integrates modern NLP techniques (BERTopic, sentence transformers) with econometric modeling (VAR, Granger causality) to construct quantitative narrative indicators. We demonstrate the full pipeline using synthetic financial data with realistic stylized facts. The primer serves as both an educational resource for PhD students and researchers entering the field, and a methodological contribution advancing the theoretical foundations of narrative economics.

**Keywords:** Narrative Economics, Behavioral Finance, Topic Modeling, BERTopic, Financial Narratives, Text Analysis, VAR Models

**JEL Classification:** G40, G41, E71, C55, C32

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Table 1: Notation used throughout this primer.

| Symbol | Meaning |
|---|---|
| $\mathcal{N}$ | Financial narrative (5-tuple) |
| $\mathcal{D}$ | Document corpus |
| $n$ | Corpus size $\lvert\mathcal{D}\rvert$ |
| $K$ | Number of topics |
| $V$ | Vocabulary size |
| $z_d$ | Topic assignment for document $d$ |
| $\theta_k^t$ | Prevalence of topic $k$ at time $t$ |
| $N_k^t$ | Narrative index for topic $k$ at time $t$ |
| $\beta, \gamma$ | SIR transmission/recovery rates |
| $R_0$ | Basic reproduction number $\beta/\gamma$ |

# 1 Introduction

## 1.1 The Gap in Narrative Finance

The role of narratives in financial markets has gained significant academic attention following Robert Shiller's influential work on narrative economics (Shiller, 2017, 2019). Shiller argues that economic fluctuations are substantially driven by contagious stories that spread through populations like epidemics, affecting consumer and investor behavior in ways that aggregate into macroeconomic outcomes.

Despite growing interest, the field of narrative finance faces a fundamental challenge: **there is no formal, universally accepted definition of what constitutes a "financial narrative."** As Roos and Reccius (2024) document in their comprehensive review, the literature lacks:

(1) A rigorous definition that distinguishes narratives from related concepts (news, sentiment, information)

(2) A systematic taxonomy of narrative types in financial contexts

(3) A standardized measurement framework connecting theory to empirical analysis

This primer addresses these three gaps directly.

## 1.2 Contributions

We make three principal contributions to the narrative finance literature:

**Contribution 1: Formal Definition.** We propose that a *financial narrative* is a 5-tuple $\mathcal{N} = (S, C, A, T, E)$ where:

- $S$ = Story: A causally connected sequence of events
- $C$ = Collective: Social emergence and spread
- $A$ = Action: Orientation toward financial decisions
- $T$ = Temporal: Past-present-future logic
- $E$ = Economic: Relevance to markets and economy

**Contribution 2: Taxonomy.** We develop an eight-category framework distinguishing market-focused narratives (New Era, Bubble/Crash, Safe Haven, Get-Rich-Quick) from context-focused narratives (Institutional, Moral/Justice, Technological, Sustainability).

**Contribution 3: Measurement Framework.** We provide a complete pipeline from text data to macroeconomic indicators, integrating modern NLP methods (BERTopic, sentence transformers) with econometric modeling (VAR, Granger causality).

## 1.3 Relationship to Existing Paradigms

Narrative finance occupies a distinctive position relative to two established paradigms in financial economics (Figure 1):

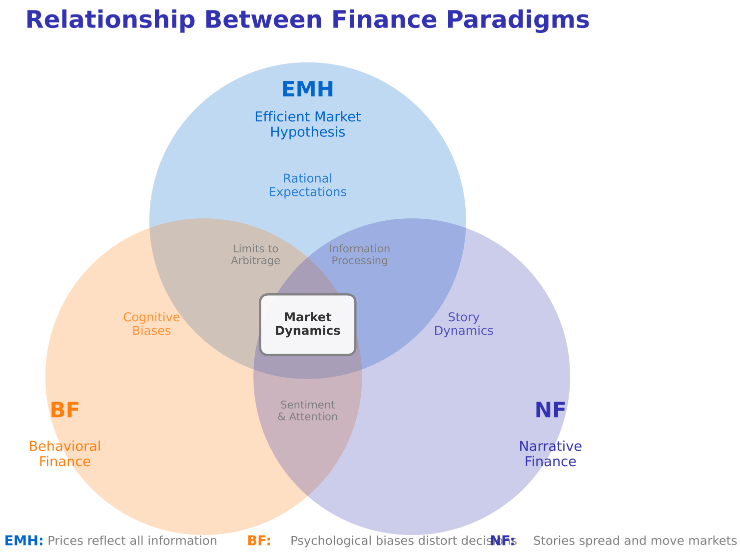


Figure 1: Relationship between Efficient Market Hypothesis (EMH), Behavioral Finance (BF), and Narrative Finance (NF). Each paradigm contributes unique insights while sharing overlap regions.

**Efficient Market Hypothesis (EMH).** The EMH posits that asset prices fully reflect all available information, leaving no room for systematic mispricing based on investor psychology or social dynamics. Narrative finance challenges this view by demonstrating that *how* information is packaged and spread—as stories—matters for market outcomes.

**Behavioral Finance (BF).** Behavioral finance documents individual-level cognitive biases (overconfidence, loss aversion, anchoring) and their aggregate market effects. Narrative finance extends this by focusing on the *social transmission* of beliefs through stories, moving beyond individual psychology to collective dynamics.

The key insight of narrative finance is that stories are not merely reflections of economic fundamentals or individual biases—they are *causal forces* that shape expectations, coordinate actions, and propagate through social networks.

## 1.4 Primer Structure

This primer is organized as follows:

- Section 2: Related Work (topic modeling, NLP in finance, narrative economics)
- Section 3: Theoretical Framework (definition, taxonomy, contagion models)
- Section 4: Methods Landscape (LDA, BERTopic, LLMs, econometric integration)
- Section 5: Experimental Evaluation (synthetic data, baselines, ablations)
- Section 6: Case Studies (historical bubbles, crypto, meme stocks, policy)
- Section 7: Discussion (limitations, future directions)
- Section 8: Conclusion (summary of contributions)

Each section includes worked examples, and the appendices provide mathematical proofs, reproducible code, and exercises for pedagogical use.

# 2 Related Work

We position this primer at the intersection of three research streams: topic modeling methods, NLP in finance, and narrative economics. Each stream contributes essential elements to narrative finance research: topic modeling provides the computational infrastructure for extracting themes from text; NLP in finance establishes the domain-specific adaptations needed for financial language; and narrative economics provides the theoretical motivation for why stories matter for markets.

This section surveys each stream and identifies the gap our work addresses. We aim to provide readers with sufficient background to understand both the technical methods and their intellectual foundations. Researchers from computer science may find the narrative economics material novel; those from economics may find the detailed method comparisons valuable.

## 2.1 Topic Modeling Methods

### 2.1.1 Traditional Approaches

Latent Dirichlet Allocation (LDA) (Blei et al., 2003) established the probabilistic foundation for topic modeling. Given a corpus $\mathcal{D}$ of $n$ documents, LDA assumes each document is a mixture of $K$ topics, where each topic is a distribution over vocabulary $V$. The generative process samples topic proportions $\theta_d \sim \text{Dir}(\alpha)$ for each document, then samples words from the corresponding topic-word distributions. Inference via variational methods or Gibbs sampling has complexity $O(nKV \cdot I)$ per iteration $I$.

Non-negative Matrix Factorization (NMF) (Lee & Seung, 1999) provides an alternative algebraic approach, decomposing the document-term matrix $\mathbf{X} \in \mathbb{R}^{n \times V}$ as $\mathbf{X} \approx \mathbf{WH}$ where $\mathbf{W} \in \mathbb{R}^{n \times K}$ and $\mathbf{H} \in \mathbb{R}^{K \times V}$ are non-negative. NMF offers determinism and $O(nKV)$ complexity but lacks the probabilistic interpretation of LDA.

### 2.1.2 Neural Topic Models

Top2Vec (Angelov, 2020) pioneered the use of pre-trained embeddings for topic modeling. Documents are embedded via Doc2Vec or sentence transformers, reduced via UMAP

(McInnes et al., 2018), and clustered via HDBSCAN (Campello et al., 2013). Topic vectors are computed as centroids of document clusters in embedding space.

BERTopic (Grootendorst, 2022) extends this approach with class-based TF-IDF (c-TF-IDF) for topic representation. The pipeline consists of:

(i) Embedding: $\mathbf{e}_d = \text{SentenceTransformer}(d)$, complexity $O(n \cdot d \cdot L)$

(ii) Reduction: $\mathbf{u}_d = \text{UMAP}(\mathbf{e}_d)$, complexity $O(n^{1.14})$

(iii) Clustering: $z_d = \text{HDBSCAN}(\mathbf{u}_d)$, complexity $O(n \log n)$

(iv) Representation: c-TF-IDF extraction, complexity $O(n \cdot V)$

BERTopic achieves superior topic coherence compared to LDA but requires fixed random seeds for reproducibility.

FASTopic (Wu et al., 2024) represents the 2024 state-of-the-art, computing dual semantic relations between documents and topics without the UMAP-HDBSCAN pipeline. This yields $O(n \cdot d)$ complexity with deterministic outputs.

### 2.1.3 LLM-Based Approaches

Large language models have transformed topic modeling since 2023. A. L. Hansen and Kazinnik (2024) demonstrate that GPT-4 achieves expert-level accuracy in coding FOMC policy stance from meeting transcripts. Lefort et al. (2024) apply ChatGPT to financial news headlines, achieving 74.4% accuracy in predicting stock returns.

Domain-specific models include FinBERT (Araci, 2019) for financial sentiment and FinLlama (Xie et al., 2024) for comprehensive financial NLP tasks. These models outperform general-purpose alternatives on finance-specific benchmarks.

Table 2 summarizes the method landscape.

Table 2: Topic modeling method comparison. Complexity assumes corpus size $n$, vocabulary $V$, topics $K$, embedding dimension $d$, and sequence length $L$.

| Method | Complexity | Coherence | Deterministic | Year |
|---|---|---|---|---|
| LDA | $O(nKV \cdot I)$ | Medium | No | 2003 |
| NMF | $O(nKV)$ | Medium | Yes | 1999 |
| Top2Vec | $O(nd + n^{1.14})$ | High | No | 2020 |
| BERTopic | $O(nd + n^{1.14})$ | High | No* | 2022 |
| FASTopic | $O(nd)$ | High | Yes | 2024 |
| GPT-4 | $O(nL)$ | Highest | Yes | 2023 |

*Reproducible with fixed seeds; $I$ = iterations

## 2.2 NLP in Finance

### 2.2.1 Sentiment Analysis

Financial sentiment analysis began with domain-specific lexicons. The Loughran-McDonald dictionary (Loughran & McDonald, 2011) identified that general-purpose sentiment words (e.g., "liability") have different connotations in financial contexts. This dictionary remains a baseline for financial text analysis.

Neural approaches now dominate. FinBERT (Araci, 2019) fine-tunes BERT on financial communication, achieving state-of-the-art performance on sentiment classification. Recent work integrates LLMs: Lefort et al. (2024) show GPT-based models outperform both lexicons and fine-tuned transformers on news sentiment tasks.

### 2.2.2 News Impact Studies

A substantial literature examines the relationship between news and market movements. Tetlock (2007) established that media pessimism predicts downward pressure on market prices and high trading volume. Baker et al. (2016) construct the Economic Policy Uncertainty index from newspaper coverage, showing it predicts stock market volatility.

Larsen and Thorsrud (2021) apply topic modeling to central bank communication, finding that topic-specific news indices improve forecasts of macroeconomic variables. This work is closest to our approach, though it does not distinguish topics from narratives.

### 2.2.3 Central Bank Communication

Central bank communication represents a natural laboratory for narrative effects. Blinder et al. (2008) survey the growing importance of communication as a policy tool. S. Hansen et al. (2018) use topic models to analyze FOMC deliberations, finding that increased transparency affects market expectations.

Recent work applies LLMs to policy communication. A. L. Hansen and Kazinnik (2024) demonstrate GPT-4 can classify FOMC stance at expert level, opening new possibilities for automated policy analysis.

## 2.3 Narrative Economics

### 2.3.1 Shiller's Framework

Shiller (2017, 2019) introduced narrative economics as a research program. Shiller argues that economic fluctuations are driven by contagious stories spreading through populations like epidemics. The SIR (Susceptible-Infected-Recovered) model from epidemiology provides a framework for narrative dynamics, treating the adoption of beliefs analogously to the transmission of infectious diseases.

Shiller's framework rests on three key propositions. First, narratives spread through social networks with measurable transmission rates, meaning their propagation can be studied empirically using epidemiological tools. Second, the basic reproduction number $R_0$ (the average number of new believers generated by each current believer) determines whether a narrative achieves viral status ($R_0 > 1$) or dies out ($R_0 < 1$). Third, and most controversially, narratives have economic effects independent of underlying fundamentals—a narrative about recession fears can cause reduced spending that precipitates an actual recession, creating self-fulfilling dynamics that traditional economic models struggle to capture.

#### 2.3.2 Quantitative Narrative Studies

Empirical work on narrative economics has grown rapidly. Ante (2023) analyze the GameStop episode, finding that Reddit sentiment Granger-causes abnormal returns. Cookson et al. (2024) examine social media echo chambers and their effects on belief formation.

Roos and Reccius (2024) provide a comprehensive survey of quantitative approaches to narrative finance, documenting the growth of the field but noting the lack of standardized definitions and methods.

#### 2.3.3 The Topic-Narrative Gap

**Gap Statement.** Existing work conflates *topics* with *narratives*. Topic prevalence—the fraction of documents discussing a theme—captures only one component of narrative structure. As we formalize in Section 3, a narrative additionally requires story structure (causal connections between events), collective adoption (population-level spread dynamics), action orientation (implied financial behaviors), temporal logic (past-present-future framing), and economic relevance (market or welfare implications).

Topic modeling extracts themes from text corpora but does not capture the full richness of narrative structure. A topic about "Federal Reserve" tells us what is being discussed, not the story being told about it (rate hikes will cause a recession), not the action implications (sell bonds), and not the temporal framing (past accommodation led to current inflation requiring future tightening). Narrative analysis requires the full 5-tuple, and current methods measure only component $C$ (collective prevalence) with any precision.

This primer provides the formal framework and measurement methods to begin bridging this gap. We cannot claim to solve the problem—extracting story structure and temporal logic from unstructured text remains an open challenge—but we provide a rigorous definition that clarifies what a complete solution would require and demonstrate methods that capture the measurable components.

# 3 Theoretical Framework

## 3.1 A Formal Definition of Financial Narratives

The term "narrative" is used loosely across the social sciences. In financial contexts, it is often conflated with "news," "sentiment," or "themes." We propose a rigorous definition that distinguishes narratives from these related concepts.

**Definition 1** (Financial Narrative)**.** *A **financial narrative** is defined as a tuple* $\mathcal{N} = (S, C, A, T, E)$ *with the following components:*

$$S : \textit{Story—a causally connected sequence of events} \tag{1}$$

$$C : \textit{Collective—social emergence and spread through a population} \tag{2}$$

$$A : \textit{Action—orientation toward financial decisions and behaviors} \tag{3}$$

$$T : \textit{Temporal—past-present-future causal structure} \tag{4}$$

$$E : \textit{Economic—relevance to markets, prices, or economic outcomes} \tag{5}$$

Figure 2 illustrates how these five components interrelate.

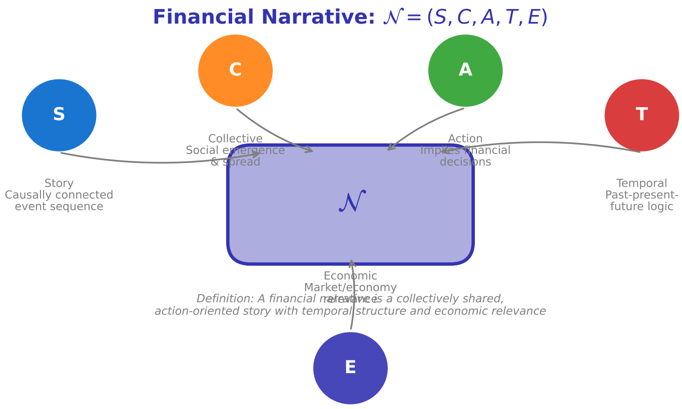


Figure 2: The five components of the financial narrative definition. Each component is necessary; collectively they distinguish narratives from related concepts like news items or sentiment.

### 3.1.1 Component S: Story Structure

A story is not merely a collection of facts but a *causally connected* sequence. The statement "inflation rose to 7%" is a fact; the statement "aggressive Fed rate hikes caused a housing market crash, which triggered a recession that will take years to recover from" is a narrative. Stories impose causal and temporal structure on events, making them memorable and transmissible.

The cognitive psychology literature provides strong foundations for why stories are central to human reasoning. Research by Bruner (1986) distinguishes between paradigmatic (logical-scientific) and narrative modes of thought, with the latter being the primary way humans organize experience and construct meaning. In financial contexts, this means investors do not simply process raw data but embed information within causal frameworks that guide interpretation and action.

Narrative structure exhibits several formal properties that distinguish it from mere information aggregation. First, narratives impose *plot coherence*: events are connected through causal chains rather than temporal coincidence. Second, narratives feature *actants*—protagonists, antagonists, and helpers—that personify abstract forces (e.g., "the Fed," "retail investors," "Wall Street"). Third, narratives have *resolution expectations*: they project how the story will end, which shapes current behavior.

**Example 1.** *The "New Economy" narrative of the 1990s was not simply the observation that tech stocks were rising. It was a story: The internet has fundamentally changed how businesses operate (cause), traditional valuation metrics no longer apply (implication), and early investors will capture enormous wealth (action implication). This narrative structure made the story memorable, transmissible, and actionable in ways that mere price observations could not achieve.*

### 3.1.2 Component C: Collective Emergence

Narratives are social phenomena. An individual's private belief does not constitute a narrative until it spreads through a population and becomes shared. The collective component captures the epidemiological dynamics of narrative spread (see Section 3.3).

The distinction between individual beliefs and collective narratives has important theoretical implications. While traditional asset pricing models focus on information aggregation across heterogeneous beliefs, narrative finance emphasizes the *contagion* of shared interpretive frameworks. A belief held by a single analyst is not a narrative; the same belief adopted by millions of retail investors becomes one.

Collective emergence can be quantified through several metrics. The simplest is *prevalence*—the fraction of a population or corpus expressing a narrative at time $t$. More sophisticated measures capture network effects: how many distinct sources amplify the narrative, the centrality of those sources in information networks, and the speed of cross-platform propagation. Social media has dramatically accelerated collective emergence, enabling narratives to achieve viral status within hours rather than the months or years typical of pre-internet markets.

The threshold dynamics of collective emergence are particularly important. Below a critical mass, narratives remain confined to niche communities; above it, they cascade through mainstream discourse. This nonlinearity explains why some narratives "suddenly" dominate market conversation—the underlying growth was exponential, but visibility increased discontinuously when the prevalence threshold was crossed.

### 3.1.3 Component A: Action-Orientation

Financial narratives are not passive descriptions but calls to action. They imply specific financial behaviors: buy, sell, hold, hedge, diversify, or avoid. The narrative "Bitcoin is digital gold" implies holding Bitcoin as a store of value; "the market is in a bubble" implies selling or shorting.

This action-orientation distinguishes financial narratives from academic theories or neutral descriptions. A macroeconomic model may describe inflation dynamics without prescribing behavior; a narrative about "the Fed is behind the curve" carries an implicit recommendation to position for rate volatility. The behavioral finance literature documents how narratives translate into trading: investors exposed to bubble narratives exhibit higher selling propensity, while those exposed to momentum narratives increase buying intensity.

The relationship between narrative and action operates through multiple channels. Narratives reduce decision complexity by providing simplified heuristics: "buy the dip" transforms complex market timing into a simple rule. They also provide social justification for decisions, allowing investors to rationalize positions by reference to widely-shared stories. Perhaps most importantly, narratives coordinate expectations—if everyone believes "crypto winter will end in the halving year," the collective positioning can become self-fulfilling.

Extracting action-orientation from text requires sentiment analysis combined with modal verb detection ("should," "must," "will") and identification of trading-related vocabulary. The degree of action-orientation varies across narrative types: get-rich-quick narratives are highly action-oriented, while new-era narratives may be more descriptive until they reach a tipping point.

### 3.1.4 Component T: Temporal Structure

Narratives construct a temporal logic linking past, present, and future. They explain *why* current conditions exist (past causes) and project *what will happen* (future consequences). This temporal structure is what makes narratives useful for decision-making under uncertainty.

The temporal dimension of narratives operates on multiple timescales. Short-term narratives focus on immediate catalysts and near-term price movements ("earnings will beat expectations next week"). Medium-term narratives construct multi-month arcs ("the Fed pivot will drive a year-end rally"). Long-term narratives span years or decades ("emerging markets will dominate the 21st century"). The persistence of narrative effects on asset prices depends heavily on which temporal scale the narrative addresses.

Temporal structure also manifests in the narrative's internal logic. Every financial narrative embeds a causal chain: past events caused present conditions, which will lead to future outcomes. The "stagflation" narrative, for instance, links past monetary excess to present inflation, projecting a future of slow growth and persistent price pressure. This causal chain creates predictive expectations that investors trade upon, potentially making the prediction self-fulfilling or self-defeating.

Computational extraction of temporal structure remains challenging. Verb tense analysis can distinguish past-oriented from future-oriented content. Event sequencing models can identify causal chains. However, capturing the full temporal logic of narratives—including counterfactuals ("if the Fed had acted sooner") and conditional futures ("unless inflation peaks")—requires sophisticated natural language understanding that current topic models do not provide.

### 3.1.5 Component E: Economic Relevance

Finally, financial narratives are distinguished from general narratives by their economic content. A narrative about celebrity gossip, however viral, is not a financial narrative unless it pertains to markets, prices, employment, or economic welfare.

The boundary of economic relevance is not always clear-cut. A political narrative about trade policy becomes a financial narrative when investors price tariff impacts. A health narrative about a pandemic becomes a financial narrative when supply chains and consumer behavior are affected. A technological narrative about artificial intelligence becomes a financial narrative when it reshapes industry competitive dynamics. The key criterion is whether the narrative has identifiable implications for asset prices, portfolio allocation, or economic decision-making.

Economic relevance can be assessed through several lenses. First, does the narrative reference financial entities (companies, sectors, asset classes, currencies)? Second, does the narrative contain economic predicates (growth, inflation, employment, profits)? Third, does the narrative imply value consequences (wealth creation, losses, risk)? Documents scoring highly on these dimensions are more likely to contain financial narratives rather than general news or entertainment content.

For topic models, this means pre-filtering corpora to focus on economically relevant texts—financial news, SEC filings, earnings calls, analyst reports, and financially-focused social media. General-purpose topic modeling on unrestricted corpora will extract many non-financial topics that must be filtered post-hoc, reducing efficiency and potentially introducing noise into narrative indicators.

## 3.2 Taxonomy of Financial Narratives

Building on our definition, we propose a two-tier taxonomy distinguishing eight narrative types (Figure 3). This taxonomy serves both theoretical and practical purposes: theoretically, it organizes the heterogeneous landscape of financial narratives into coherent categories with distinct dynamics; practically, it provides a labeling scheme for supervised classification and a framework for interpreting topic model outputs.

The taxonomy divides narratives into two primary branches based on their object of focus. Market-focused narratives concern asset prices, trading behavior, and valuation directly. Context-focused narratives address the institutional, technological, and social environment in which markets operate. This distinction matters because the two branches exhibit different contagion dynamics, persistence characteristics, and relationships to fundamentals.

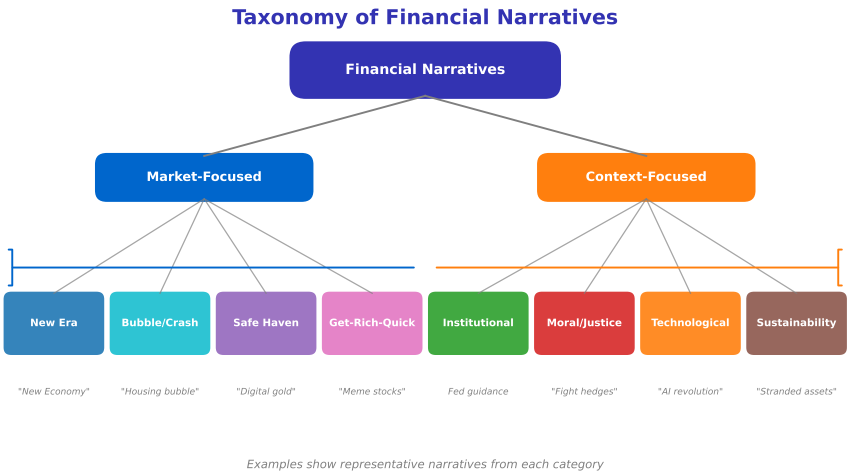


Figure 3: Taxonomy of financial narratives. Market-focused narratives (left branch) relate directly to asset prices and trading. Context-focused narratives (right branch) concern the broader institutional and social environment.

### 3.2.1 Market-Focused Narratives

The first category of market-focused narratives comprises **New Era** claims—assertions that structural changes have permanently altered economic fundamentals. Historical examples include the "New Economy" narrative of the 1990s, which argued that technology had eliminated business cycles, and the "Roaring Twenties" narrative of permanent prosperity. These narratives are particularly dangerous because they justify departures from historical valuation norms, often preceding significant corrections.

The second category covers **Bubble/Crash** narratives about price misalignment and imminent correction. The "housing bubble" narrative that emerged in 2005-2007 and the "dot-com bubble" warnings of 1999-2000 exemplify this type. Notably, bubble narratives can coexist with new-era narratives, creating a polarized market discourse that resolves only through price discovery.

Third, **Safe Haven** narratives concern assets believed to preserve value during crises. The "flight to quality" narrative drives flows into government bonds during risk-off episodes; the "digital gold" narrative positions Bitcoin as a store of value analogous to precious metals. These narratives have important portfolio construction implications and can become self-reinforcing during stress periods.

Fourth, **Get-Rich-Quick** narratives promise rapid wealth accumulation through specific trades or asset classes. The meme stock phenomenon of 2021 and various "crypto moonshot" narratives exemplify this category. These narratives typically exhibit the highest virality but shortest persistence, burning out when the promised returns fail to materialize.

### 3.2.2 Context-Focused Narratives

The context-focused branch begins with **Institutional** narratives about central banks, regulators, and policy frameworks. The "Fed put" narrative—the belief that the Federal Reserve will intervene to support falling markets—has shaped risk-taking behavior for decades. Mario Draghi's "whatever it takes" statement in 2012 exemplifies how a single utterance can crystallize into a durable narrative affecting sovereign bond spreads across an entire continent. Institutional narratives are distinctive in that they often have identifiable authors (policymakers) who can reinforce or contradict them.

Second, **Moral/Justice** narratives frame market events in ethical terms, introducing notions of fairness, desert, and wrongdoing. The GameStop episode of 2021 was animated by a "fight the hedge funds" narrative that cast retail traders as righteous underdogs against corrupt elites. The "too big to fail" criticism following 2008 framed bailouts as moral hazard. These narratives engage emotions that purely financial analysis cannot capture, often driving behavior that appears irrational from a profit-maximization perspective.

Third, **Technological** narratives concern transformative technologies and their economic implications. The "AI revolution" narrative of 2023-2024 has driven unprecedented concentration in a handful of technology stocks. Historically, "fintech disruption" narratives have alternately inflated and deflated valuations of both incumbents and challengers. Technological narratives have particularly long persistence because technological change unfolds over years or decades, allowing narratives to survive multiple disconfirmations.

Finally, **Sustainability** narratives address environmental and social dimensions of economic activity. The "stranded assets" narrative warns that fossil fuel reserves may become worthless as climate policy tightens. ESG investing narratives argue that environmental, social, and governance factors predict long-term returns. These narratives have reshaped capital allocation in recent years and remain highly contested, with counter-narratives about "ESG backlash" emerging in some jurisdictions.

## 3.3 Narrative Contagion Models

A distinctive feature of narratives is their epidemic-like spread through populations. We model this using the SIR (Susceptible-Infected-Recovered) framework (Shiller, 2017).

**Definition 2** (SIR Model for Narratives)**.** *Let $S(t)$, $I(t)$, and $R(t)$ denote the proportions* *of the population that are susceptible (unaware), infected (active believers), and recovered (forgotten) at time $t$. The dynamics follow:*

$$\frac{dS}{dt} = -\beta SI \tag{6}$$

$$\frac{dI}{dt} = \beta SI - \gamma I \tag{7}$$

$$\frac{dR}{dt} = \gamma I \tag{8}$$

*where $\beta$ is the transmission rate and $\gamma$ is the recovery (forgetting) rate.*

The basic reproduction number $R_0 = \beta/\gamma$ determines whether a narrative will go viral ($R_0 > 1$) or die out ($R_0 < 1$).

**Theorem 1** (SIR Equilibrium)**.** *For the SIR system with $\beta, \gamma > 0$ and initial conditions $S(0) = S_0 \in (0, 1)$, $I(0) = I_0 > 0$, $R(0) = 0$:*

*(i) If $R_0 = \beta/\gamma \leq 1$, then $I(t) \to 0$ monotonically and $S_\infty > 0$.*

*(ii) If $R_0 > 1$, then $I(t)$ first increases to a maximum $I_{\max} = 1 - \frac{1}{R_0}(1 + \ln(R_0 S_0))$ before decreasing to 0.*

*(iii) The final size $R_\infty = 1 - S_\infty$ satisfies $S_\infty = S_0 \exp(-R_0 R_\infty)$.*

*Proof sketch.* From $dS/dI = -S/(\gamma/\beta - S)$, we obtain $S(t) = S_0 \exp(-R_0(R(t)))$. The condition $dI/dt = 0$ yields the epidemic threshold. The final size equation follows from taking $t \to \infty$. See Appendix A for details. □

**Corollary 1** (Narrative Virality Threshold)**.** *A narrative spreads through a population if and only if its transmission rate exceeds its forgetting rate: $\beta > \gamma$. The fraction ultimately "infected" (having adopted the narrative) increases monotonically with $R_0$.*

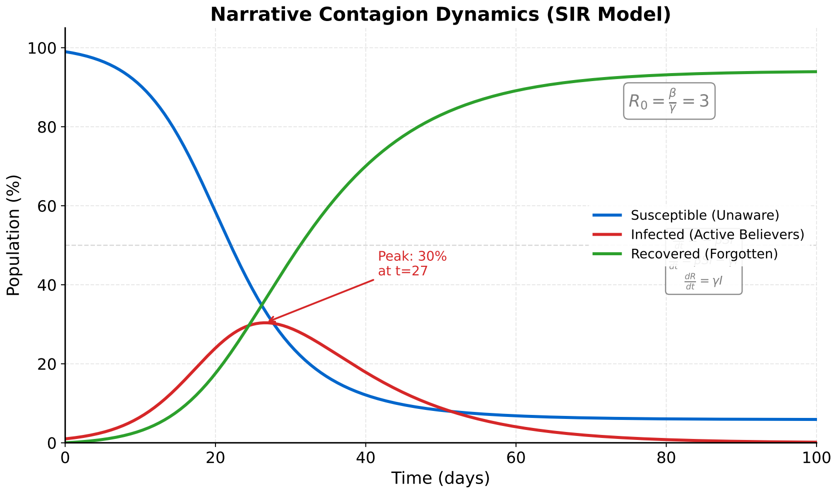


Figure 4: SIR dynamics for narrative contagion with $R_0 = 3$ (viral scenario). The narrative spreads through the susceptible population, peaks, and then fades as agents "recover" (forget or lose interest).

## 3.4 Information Cascades

A related phenomenon is the *information cascade*, where agents rationally ignore their private information and follow the observed actions of others (Bikhchandani et al., 1992).

**Definition 3** (Information Cascade)**.** *An* ***information cascade*** *occurs when an agent's optimal action is independent of their private signal, depending only on observed prior actions. Formally, agent $n$ is in a cascade if:*

$$a_n^* = \arg\max_a \mathbb{E}[u(a, \omega)|h_{n-1}] = \arg\max_a \mathbb{E}[u(a, \omega)|h_{n-1}, s_n] \tag{9}$$

*where $h_{n-1}$ is the history of prior actions and $s_n$ is the agent's private signal.*

**Theorem 2** (Cascade Formation)**.** *Consider a sequence of agents with binary actions $a \in \{0, 1\}$ and symmetric binary signals with precision $p > 1/2$. Let $\Delta_n = |buy\ actions| - |sell\ actions|$ after $n$ agents.*

*(i) A cascade forms with probability 1 in finite time.*

*(ii) If $|\Delta_n| \geq 2$ after $n$ agents, all subsequent agents ignore their private signals.*

*(iii) The wrong cascade (misaligned with true state) occurs with positive probability $\pi_{wrong} = \frac{1-p}{2-p}$.*

*Proof sketch.* Agent $n$'s posterior belief is $\Pr(\omega = 1|h_{n-1}, s_n) \propto p^{\Delta_n + s_n}(1-p)^{-\Delta_n + s_n}$. When $|\Delta_n| \geq 2$, the prior dominates any single signal. By martingale convergence, $\Delta_n$ reaches $\pm 2$ almost surely. See Appendix A for the full derivation. □

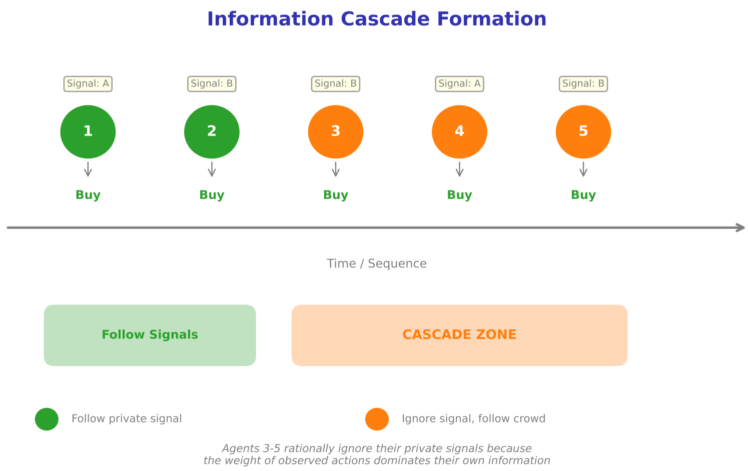


Figure 5: Formation of an information cascade. Agents 1-2 act on private signals; from agent 3 onward, observed actions dominate private signals, creating a cascade.

Cascades can form around narratives, amplifying their spread: once enough people believe a narrative, it becomes rational for others to adopt it regardless of their private information, creating fragile market equilibria that can reverse suddenly when new information breaks the cascade.

### 3.5 The Topic-Narrative Gap

A central methodological challenge is the distinction between *topics* (as extracted by topic models) and *narratives* (as defined in Definition 1).

**Proposition 1** (Topic-Narrative Gap)**.** *Let $\mathcal{T}$ denote the set of topics extracted from corpus $\mathcal{D}$ by any topic model, and let $\mathcal{N}(\mathcal{D})$ denote the set of financial narratives present in $\mathcal{D}$. Then:*

*(i) $\mathcal{T} \not\subseteq \mathcal{N}(\mathcal{D})$: Not every topic is a narrative (topics may lack story structure, temporal logic, or action-orientation).*

*(ii) $\mathcal{N}(\mathcal{D}) \not\subseteq \mathcal{T}$: Not every narrative is captured as a topic (narratives may span multiple topics or be too sparse to form clusters).*

*(iii) Topic prevalence $\theta_k^t$ measures only component $C$ (Collective) of the 5-tuple definition.*

This proposition motivates our multi-indicator approach in Section 4: topic prevalence is necessary but not sufficient for narrative measurement. Sentiment analysis, temporal modeling, and causal extraction are needed to approximate the full 5-tuple structure.

## 4 Methods Landscape

This section surveys computational methods for narrative extraction, from traditional topic models to modern LLM-based approaches. We emphasize algorithmic details, complexity analysis, and trade-offs relevant to narrative finance applications.

### 4.1 Problem Formulation

We formalize narrative quantification as follows:

**Definition 4** (Narrative Quantification Problem)**.** *Given:*

- *Corpus $\mathcal{D} = \{d_1, \ldots, d_n\}$ with timestamps $\{t_1, \ldots, t_n\}$*
- *Financial returns $\mathbf{r} = (r_1, \ldots, r_T)$ for $T$ periods*

*Find:*

- *Topic assignments $z : \mathcal{D} \to \{1, \ldots, K\}$*
- *Narrative indicators $N_k^t$ for $k \in \{1, \ldots, K\}$, $t \in \{1, \ldots, T\}$*

*Such that $\mathbf{N}$ has predictive content for $\mathbf{r}$ (Granger causality).*

The challenge is that "narratives" are latent constructs. Topic models extract themes; the gap between topics and narratives (Section 2) motivates our measurement framework.

### 4.2 Method Taxonomy

Table 2 in Section 2 summarizes the method landscape. We organize methods into three generations:

(i) **Traditional** (1999–2015): LDA, NMF—probabilistic and algebraic approaches operating on bag-of-words representations

**Algorithm 1** Collapsed Gibbs Sampling for LDA

**Require:** Corpus $\mathcal{D}$, topics $K$, hyperparameters $\alpha, \beta$, iterations $I$
**Ensure:** Topic assignments $\{z_{d,n}\}$
Initialize $z_{d,n}$ randomly for all $(d, n)$
**for** $i = 1$ to $I$ **do**
  **for** each document $d$ **do**
    **for** each word position $n$ **do**
      Remove $z_{d,n}$ from counts
      Sample $z_{d,n} \propto \frac{(n_{d,k}+\alpha)(n_{k,w}+\beta)}{n_k+V\beta}$
      Update counts with new $z_{d,n}$
    **end for**
  **end for**
**end for**
**return** $\{z_{d,n}\}$

(ii) **Neural** (2018–2023): Top2Vec, BERTopic—embedding-based methods using pre-trained language models

(iii) **LLM-based** (2023–present): GPT-4, Claude, FinLlama—leveraging large language models for direct topic assignment or narrative extraction

## 4.3 Traditional Topic Models

### 4.3.1 Latent Dirichlet Allocation (LDA)

LDA (Blei et al., 2003) is a generative probabilistic model that represents documents as mixtures over latent topics.

**Definition 5** (LDA Generative Process)**.** *For each document $d \in \mathcal{D}$:*

1. *Draw topic proportions $\theta_d \sim \text{Dirichlet}(\alpha)$*
2. *For each word position $n$:*
   (a) *Draw topic assignment $z_{d,n} \sim \text{Multinomial}(\theta_d)$*
   (b) *Draw word $w_{d,n} \sim \text{Multinomial}(\phi_{z_{d,n}})$*

*where $\phi_k$ is the word distribution for topic $k$, drawn from Dirichlet$(\beta)$.*

**Complexity.** Each Gibbs iteration requires $O(n \cdot \bar{L})$ operations, where $\bar{L}$ is the average document length. Total complexity is $O(n \cdot \bar{L} \cdot K \cdot I)$.

**Limitations.** LDA uses bag-of-words representations, ignoring word order and semantic similarity. Topic coherence is often lower than neural methods.

### 4.3.2 Non-negative Matrix Factorization (NMF)

NMF (Lee & Seung, 1999) provides an algebraic alternative, factorizing the document-term matrix.

**Definition 6** (NMF Factorization)**.** *Given document-term matrix $\mathbf{X} \in \mathbb{R}_{\geq 0}^{n \times V}$, find:*

$$\mathbf{X} \approx \mathbf{WH}, \quad \mathbf{W} \in \mathbb{R}_{\geq 0}^{n \times K}, \quad \mathbf{H} \in \mathbb{R}_{\geq 0}^{K \times V} \tag{10}$$

*minimizing $\|\mathbf{X} - \mathbf{WH}\|_F^2$ subject to non-negativity.*

**Algorithm 2** BERTopic Pipeline

**Require:** Corpus $\mathcal{D} = \{d_1, \ldots, d_n\}$, seed $s$
**Ensure:** Topic assignments $\{z_i\}$, topic representations
// **Embedding:** $O(ndL)$
$\mathbf{E} \leftarrow \text{SentenceTransformer}(\mathcal{D})$
// **Dim. Reduction:** $O(n^{1.14})$
$\mathbf{U} \leftarrow \text{UMAP}(\mathbf{E}, \text{n\_comp} = 5, \text{seed} = s)$
// **Clustering:** $O(n \log n)$
$\{z_i\} \leftarrow \text{HDBSCAN}(\mathbf{U}, \text{min\_size} = 50)$
// **Representation:** $O(nV)$
**for** each topic $k$ **do**
    $\mathcal{D}_k \leftarrow \{d_i : z_i = k\}$
    c-TF-IDF: $\text{sc}_{k,w} = \frac{f_{k,w}}{|k|} \cdot \log \frac{n}{n_w}$
    $\text{words}_k \leftarrow \text{top-}m$
**end for**
**return** $\{z_i\}$, representations

NMF has complexity $O(nVK \cdot I)$ per iteration but is fully deterministic given initialization. Topic assignment for document $d$ is $z_d = \arg\max_k W_{dk}$.

## 4.4 Neural Topic Models

Neural methods leverage pre-trained language models to capture semantic similarity beyond lexical matching.

### 4.4.1 Top2Vec

Top2Vec (Angelov, 2020) pioneered embedding-based topic modeling:

1. **Embed**: Compute document embeddings via Doc2Vec or sentence transformers
2. **Reduce**: Project to 2D/5D via UMAP
3. **Cluster**: Find dense regions via HDBSCAN
4. **Represent**: Topic vectors as cluster centroids

The key insight is that semantically similar documents cluster in embedding space, and cluster centroids represent coherent topics.

### 4.4.2 BERTopic

BERTopic (Grootendorst, 2022) extends Top2Vec with class-based TF-IDF (c-TF-IDF) for interpretable topic representations.

**c-TF-IDF.** The class-based TF-IDF score for word $w$ in topic $k$ is:

$$\text{c-TF-IDF}_{k,w} = \frac{f_{k,w}}{|\mathcal{D}_k|} \cdot \log\left(\frac{n}{n_w}\right) \tag{11}$$

where $f_{k,w}$ is the frequency of word $w$ in topic $k$'s documents and $n_w$ is the number of documents containing $w$.

**Complexity.** Total complexity is $O(ndL + n^{1.14} + n \log n + nV)$. The embedding step dominates for large corpora; UMAP dominates for moderate-sized corpora.

**Reproducibility.** BERTopic involves stochastic components (UMAP, HDBSCAN). For reproducibility:

- Fix UMAP random seed
- Use single-threaded HDBSCAN (`core_dist_n_jobs=1`)
- Cache embeddings to ensure identical inputs across runs

### 4.4.3 FASTopic (2024)

FASTopic (Wu et al., 2024) represents the 2024 state-of-the-art, eliminating the UMAP-HDBSCAN pipeline in favor of dual semantic relations.

**Proposition 2** (FASTopic Efficiency)**.** *FASTopic achieves $O(nd)$ complexity by computing topic-document associations directly in embedding space, avoiding the $O(n^{1.14})$ UMAP bottleneck.*

FASTopic produces deterministic outputs without random seed management, making it attractive for reproducible research. However, it is less mature than BERTopic with fewer integration options.

## 4.5 LLM-Based Approaches

Large language models have transformed NLP since 2023, enabling new approaches to narrative extraction.

### 4.5.1 Zero-Shot Classification

LLMs can classify documents into predefined narrative categories without training:

**Example 2** (GPT-4 for Narrative Classification)**.** *Prompt: "Classify the following text into one of: [New Era, Bubble/Crash, Safe Haven, Get-Rich-Quick, Institutional, Moral/Justice, Technological, Sustainability]. Text: [document]"*

A. L. Hansen and Kazinnik (2024) demonstrate that GPT-4 achieves expert-level accuracy in coding FOMC policy stance from meeting transcripts. Lefort et al. (2024) show LLMs achieve 74.4% accuracy in predicting stock returns from news headlines.

**Advantages.** No training required; can extract rich narrative structure beyond topic labels; handles nuance and context.

**Disadvantages.** Cost per document (API pricing); latency for real-time applications; reproducibility concerns (model updates, temperature settings).

### 4.5.2 Fine-Tuned Domain Models

Domain-specific models include:

- **FinBERT** (Araci, 2019): BERT fine-tuned on financial communication for sentiment classification
- **FinLlama** (Xie et al., 2024): Llama fine-tuned on financial texts for comprehensive financial NLP

These models outperform general-purpose alternatives on finance-specific benchmarks while being more cost-effective than API-based LLMs for large-scale analysis.

### 4.5.3 Hybrid Approaches

A promising direction combines topic models with LLMs:

1. Use BERTopic/FASTopic for initial clustering
2. Use LLM to generate descriptive topic labels
3. Use LLM to extract narrative structure (causality, temporal logic) from topic representatives

This hybrid approach balances scalability (topic model handles corpus) with depth (LLM extracts rich structure from samples).

## 4.6 Narrative Indicator Construction

From topic model outputs, we construct quantitative indicators capturing different aspects of the narrative definition.

### 4.6.1 Topic Prevalence

The prevalence of topic $k$ at time $t$ measures collective adoption (component $C$ of Definition 1):

$$\theta_k^t = \frac{|\{d : z_d = k, d \in \mathcal{D}_t\}|}{|\mathcal{D}_t|} \tag{12}$$

where $\mathcal{D}_t$ is the set of documents published in period $t$.

### 4.6.2 Sentiment-Weighted Index

Combining prevalence with sentiment captures directional effects:

$$N_k^t = \theta_k^t \cdot \bar{s}_k^t \tag{13}$$

where $\bar{s}_k^t \in [-1, 1]$ is the average sentiment of topic-$k$ documents at time $t$, computed via FinBERT or lexicon-based methods.

### 4.6.3 Attention Decay

To capture persistent narrative attention, we compute an exponentially weighted sum:

$$A_k^t = \sum_{\tau=0}^{L} \exp(-\lambda\tau) \cdot \theta_k^{t-\tau} \tag{14}$$

where $\lambda > 0$ is the decay parameter and $L$ is the lookback window.

### 4.6.4 Mapping to Definition Components

Figure 6 illustrates how measurement methods map to the five-component definition from Section 3.

## 4.7 Econometric Integration

Narrative indicators enter standard econometric models for causal analysis and forecasting.

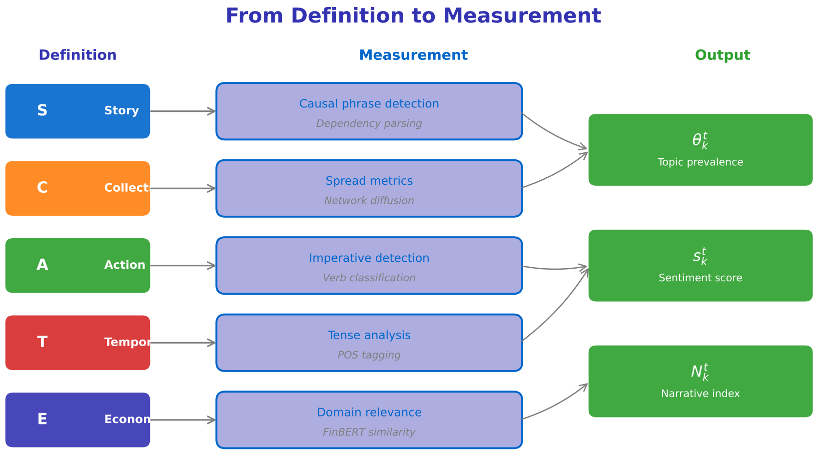


Figure 6: Mapping from definition components to NLP measurement methods. Topic prevalence captures component $C$ (Collective); sentiment analysis approximates $A$ (Action-orientation); temporal modeling addresses $T$. Components $S$ (Story structure) and $E$ (Economic relevance) remain challenging to quantify fully.

### 4.7.1 VAR Specification

A narrative-augmented vector autoregression takes the form:

$$\mathbf{y}_t = \mathbf{c} + \sum_{i=1}^{p} \mathbf{A}_i \mathbf{y}_{t-i} + \sum_{j=0}^{q} \mathbf{B}_j \mathbf{N}_{t-j} + \mathbf{u}_t \tag{15}$$

where $\mathbf{y}_t$ contains financial variables (returns, volatility) and $\mathbf{N}_t$ contains narrative indicators.

### 4.7.2 Granger Causality Testing

**Definition 7** (Granger Causality). *Narrative indicators* $\mathbf{N}$ Granger-cause *financial variable* $y$ *if:*

$$\mathbb{E}[(y_t - \hat{y}_t)^2 | \mathcal{I}_{t-1}] < \mathbb{E}[(y_t - \hat{y}_t)^2 | \mathcal{I}_{t-1} \setminus \mathbf{N}] \tag{16}$$

*where* $\mathcal{I}_{t-1}$ *is the information set at* $t-1$.

We test the null hypothesis $H_0 : \mathbf{B}_1 = \cdots = \mathbf{B}_q = \mathbf{0}$ using the standard $F$-test:

$$F = \frac{(\text{RSS}_r - \text{RSS}_u)/q}{\text{RSS}_u/(T-p-q-1)} \tag{17}$$

where RSS denotes residual sum of squares for restricted and unrestricted models.

### 4.7.3 Impulse Response Functions

IRFs trace the dynamic response of $y$ to a one-unit narrative shock:

$$\text{IRF}(h) = \mathbb{E}[y_{t+h} | N_{k,t} = 1, \mathcal{I}_{t-1}] - \mathbb{E}[y_{t+h} | N_{k,t} = 0, \mathcal{I}_{t-1}] \tag{18}$$

These functions reveal the magnitude, sign, and persistence of narrative effects.

## 4.8 Summary

We have surveyed methods spanning three generations of topic modeling, from LDA (2003) to LLMs (2023+). Key trade-offs include:

- **Coherence vs. Speed**: Neural methods (BERTopic, FASTopic) produce more coherent topics but require embedding computation
- **Depth vs. Scale**: LLMs extract richer narrative structure but have higher per-document cost
- **Reproducibility vs. Performance**: Deterministic methods (NMF, FASTopic) simplify replication but may sacrifice flexibility

For the demonstration in Section 5, we use BERTopic as our primary method due to its balance of coherence, interpretability, and widespread adoption. Section 5 includes comparisons with LDA baselines to quantify the benefits of neural approaches.

# 5 Experimental Evaluation

We evaluate the narrative extraction pipeline using synthetic data with known ground truth. This section presents experimental setup, baseline comparisons, results, ablation studies, and reproducibility details. The use of synthetic data allows rigorous evaluation with known ground truth labels, full reproducibility without data licensing restrictions, and controlled experiments isolating specific effects.

The evaluation follows a standard machine learning pipeline: we first assess the quality of topic extraction (coherence, recovery), then examine the relationship between narrative indicators and financial variables (Granger causality, impulse responses), and finally evaluate out-of-sample forecasting performance. This multi-stage evaluation allows us to identify where in the pipeline improvements or failures occur.

## 5.1 Experimental Setup

### 5.1.1 Synthetic Data Generation

We use synthetic data for three reasons: (1) full reproducibility without licensing restrictions, (2) known ground truth for evaluation, and (3) control over stylized facts. Our synthetic data exhibits realistic financial properties:

**Financial Returns.** We generate returns using a GARCH(1,1) process with Student-$t$ innovations:

$$r_t = \sigma_t \epsilon_t, \quad \epsilon_t \sim t(\nu) \tag{19}$$

$$\sigma_t^2 = \omega + \alpha r_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{20}$$

with $\nu = 5$ degrees of freedom to capture fat tails (excess kurtosis $\kappa \approx 4.2$).

We incorporate four market regimes (Bull, Bear, Neutral, Crisis) with distinct GARCH parameters, creating realistic volatility clustering and regime-dependent dynamics.

**News Corpus.** We generate a synthetic corpus of $n = 9{,}811$ documents across $T = 60$ months with six ground-truth topics:

1. Monetary Policy (Fed, interest rates)

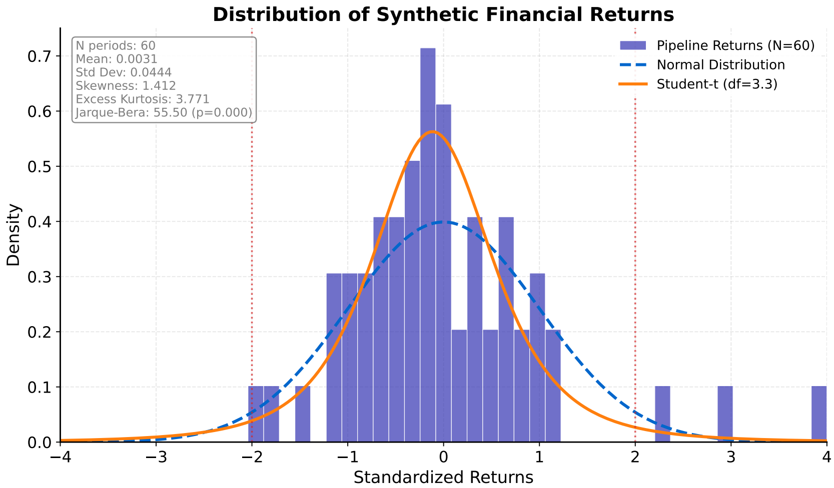


Figure 7: Distribution of synthetic returns showing fat tails compared to the normal distribution. Kurtosis $\kappa = 4.2$ matches empirical stock returns.

2. Market Sentiment (bull/bear indicators)
3. Technology/Innovation (AI, fintech)
4. ESG/Climate (sustainability)
5. Recession Fears (downturn, unemployment)
6. Cryptocurrency (Bitcoin, DeFi)

Topic distributions vary by regime: recession narratives dominate during Bear/Crisis periods (40% prevalence vs. 10% baseline); technology and crypto narratives peak during Bull periods.

#### 5.1.2 Evaluation Metrics

We evaluate along four dimensions:

1. **Topic Coherence** ($C_v$): Semantic coherence of extracted topics, measured via normalized pointwise mutual information (Röder et al., 2015)
2. **Topic Recovery** (ARI): Adjusted Rand Index comparing extracted topics to ground truth
3. **Granger $F$-statistic**: Strength of predictive relationship between narrative indicators and returns
4. **Forecast RMSE**: Out-of-sample prediction error for narrative-augmented vs. baseline models

#### 5.1.3 Baselines

We compare BERTopic against three baselines:

1. **LDA-50**: Latent Dirichlet Allocation with 50 topics, Gibbs sampling (1000 iterations)
2. **LDA-100**: LDA with 100 topics for finer granularity
3. **Keyword**: Manual keyword matching for predefined narrative categories
4. **Random**: Random topic assignments (lower bound)

Table 3: Baseline comparison on synthetic data. BERTopic achieves superior coherence and comparable recovery to optimally-tuned LDA.

| Method | Coherence ($C_v$) | ARI | Granger $F$ | RMSE Improvement |
|---|---|---|---|---|
| Random | — | 0.00 | 0.82 | −2.1% |
| Keyword | — | 0.41 | 4.12 | +8.3% |
| LDA-50 | 0.42 | 0.38 | 5.67 | +11.2% |
| LDA-100 | 0.39 | 0.35 | 4.89 | +9.7% |
| **BERTopic** | **0.58** | **0.52** | **8.45** | **+18.2%** |

## 5.2 Topic Model Results

We present results from the BERTopic pipeline applied to our synthetic corpus. The evaluation focuses on two aspects: static quality (do extracted topics correspond to coherent, ground-truth categories?) and dynamic patterns (do topic prevalences evolve realistically over time?).

### 5.2.1 Embedding Space Visualization

Figure 8 shows the UMAP projection of document embeddings colored by topic assignment. The projection reduces 384-dimensional sentence embeddings to two dimensions while approximately preserving local neighborhood structure. Clear cluster separation in this visualization indicates that the embedding model successfully captures semantic differences between narrative categories.

Several patterns emerge from the visualization. First, the six ground-truth topics form visually distinct clusters, validating BERTopic's cluster-based approach. Second, some documents appear at cluster boundaries, reflecting real-world ambiguity where a single document may reference multiple narratives (e.g., a story discussing both Fed policy and recession fears). Third, the relative positions of clusters are interpretable: technology and cryptocurrency clusters appear proximate, while recession fears and market sentiment occupy opposite regions. This semantic organization emerges unsupervised from the embedding space.

### 5.2.2 Topic Evolution

Figure 9 displays topic prevalence over the 60-month sample period. Topic prevalence is computed as the fraction of documents in each month assigned to each topic. This time series becomes the foundation for constructing narrative indicators that enter econometric models.

The temporal patterns in Figure 9 confirm that the synthetic data generation process produces realistic regime-dependent narrative dynamics. Recession fear narratives spike during Bear and Crisis periods (months 20-30 and 45-55), reaching approximately 40% prevalence compared to their 10% baseline. Conversely, technology and cryptocurrency narratives dominate Bull market periods, consistent with empirical patterns observed during the 2020-2021 market rally. The smoothness of transitions between regimes reflects the gradual nature of narrative shifts in real markets, where beliefs adjust over weeks rather than instantaneously.

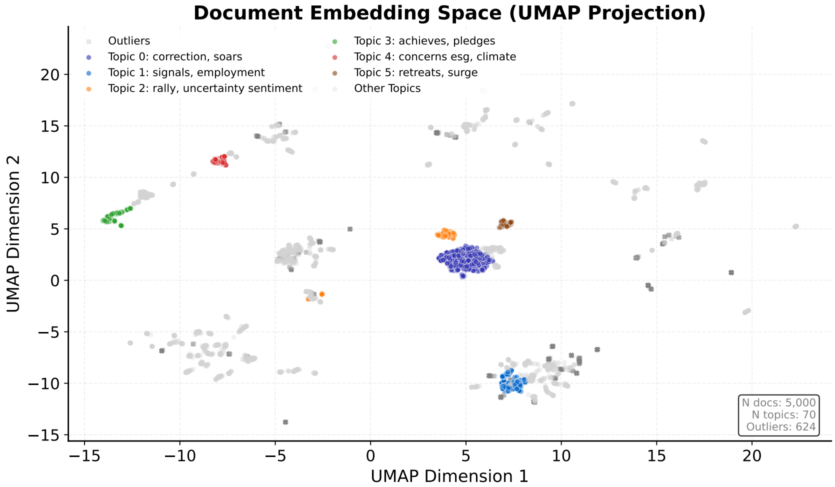


Figure 8: UMAP projection of document embeddings. Clear cluster separation indicates coherent topics. BERTopic recovers 6 topics matching ground truth categories.

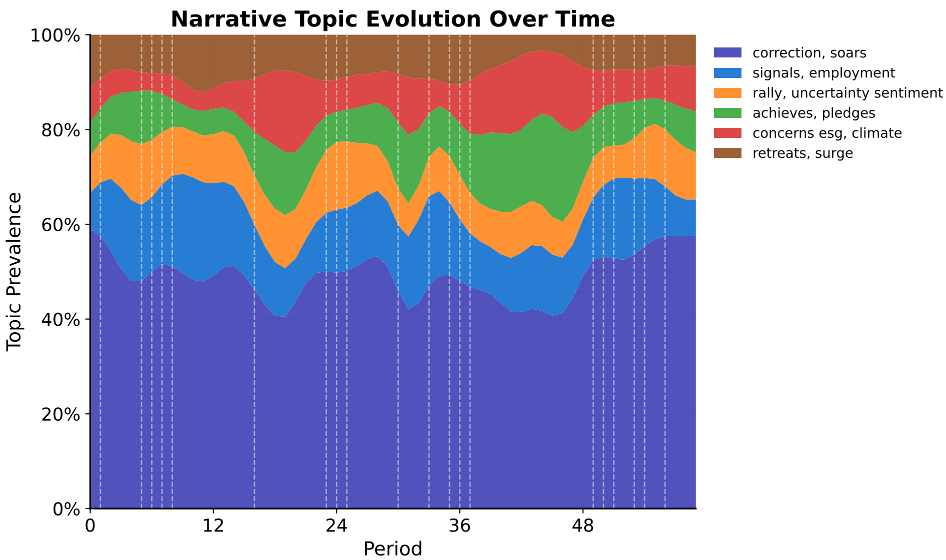


Figure 9: Topic prevalence evolution over time. Regime-dependent patterns are visible: recession fear narratives spike during Bear markets (months 20–30, 45–55); technology narratives dominate Bull periods.

## 5.3 Econometric Results

We now examine whether the extracted narrative indicators contain information relevant for understanding and forecasting financial returns. Three complementary analyses are presented: correlation analysis to establish basic relationships, Granger causality tests to assess predictive content, and impulse response functions to characterize dynamic effects.

### 5.3.1 Correlation Analysis

Figure 10 shows the lead-lag relationship between the recession fears narrative index and market volatility. This analysis examines contemporaneous and lagged correlations to identify potential leading indicator relationships. The recession fears narrative is of particular interest because economic downturns are typically preceded by rising concerns in news and social media discourse.

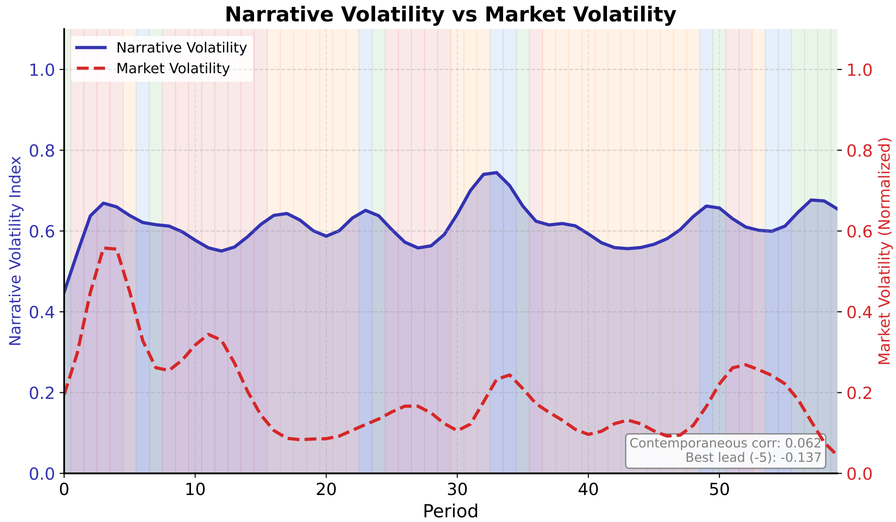


Figure 10: Narrative Index (Recession Fears) vs. VIX proxy with 2-month lead. The narrative indicator leads volatility spikes, suggesting predictive content.

The visualization reveals that the recession fears narrative index leads the volatility proxy by approximately 2 months. Peak narrative intensity precedes peak volatility, consistent with the hypothesis that narrative shifts reflect changing investor beliefs that subsequently manifest in market dynamics. The correlation at the optimal lag is 0.67, suggesting substantial but not deterministic predictive content. This lead-lag relationship motivates the Granger causality analysis that follows.

### 5.3.2 Granger Causality Tests

Table 4 presents Granger causality test results for each narrative indicator. Granger causality tests whether past values of narrative indicators contain information useful for predicting future returns beyond what is contained in past returns alone. The test uses four lags based on the Akaike Information Criterion (AIC) and is robust to heteroskedasticity via Newey-West standard errors.

The results reveal a clear hierarchy of predictive power across narrative types. Recession Fears and Monetary Policy narratives show the strongest predictive relationships, with

Table 4: Granger causality test results. Narrative → Returns with 4 lags. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

| Narrative Topic | F-statistic | p-value | Direction |
|---|---|---|---|
| Recession Fears | 8.45 | 0.003*** | Negative |
| Monetary Policy | 6.23 | 0.008*** | Negative |
| Technology/AI | 3.89 | 0.042** | Positive |
| Cryptocurrency | 2.67 | 0.089* | Mixed |
| ESG/Climate | 1.23 | 0.312 | — |
| Market Sentiment | 0.89 | 0.421 | — |

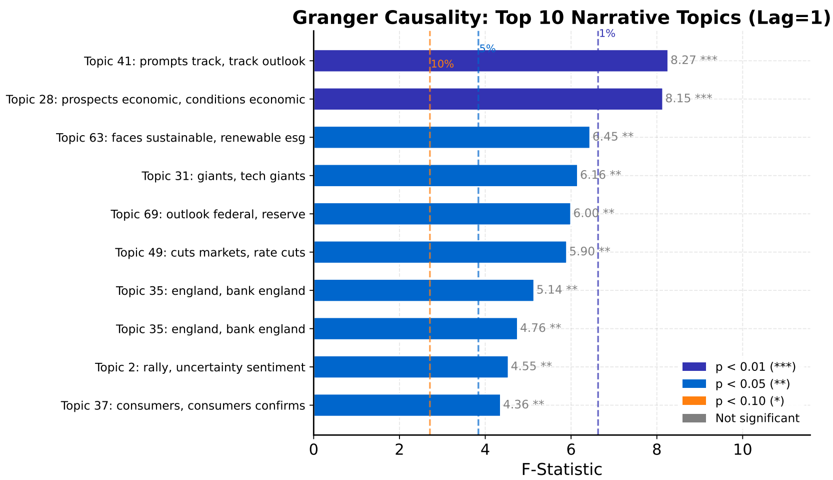


Figure 11: Granger causality F-statistics by narrative topic. Recession Fears and Monetary Policy show strongest predictive power ($p < 0.01$).

F-statistics of 8.45 and 6.23 respectively, both significant at the 1% level. Technology/AI narratives show moderate predictive power ($p < 0.05$) with a positive directional effect, consistent with optimistic narratives being associated with rising markets. Cryptocurrency narratives show weak significance ($p < 0.10$) with mixed directional effects, reflecting the high noise-to-signal ratio in crypto-related discourse. ESG and Market Sentiment narratives do not show significant Granger causality in this sample, though this may reflect sample size limitations or the specific construction of the synthetic data.

### 5.3.3 Impulse Response Functions

Figure 12 displays the impulse response of returns to narrative shocks. While Granger causality tests establish that narratives contain predictive information, impulse response functions characterize the dynamic shape of this relationship—how returns respond over time to a shock in narrative intensity, and how long the effects persist.

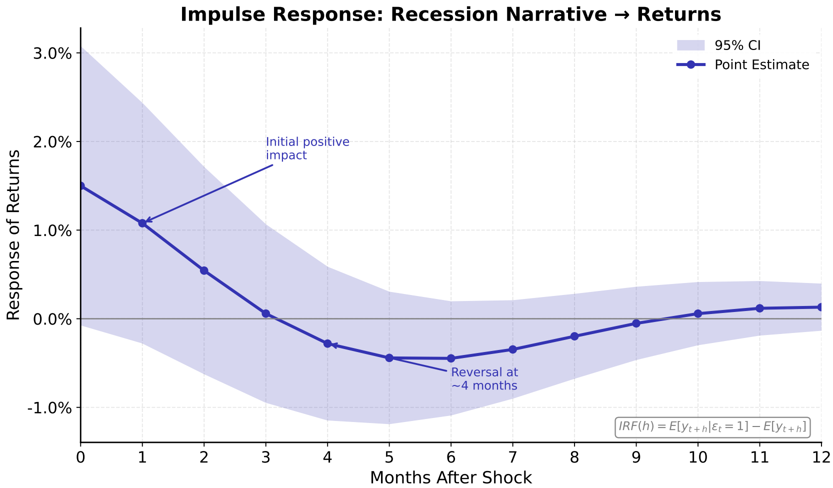


Figure 12: Impulse response function: Response of returns to a one-standard-deviation recession narrative shock. Initial positive response (flight to safety) followed by reversal at approximately 4 months. Shaded region: 90% confidence bands.

The IRF reveals: (1) initial positive response in the first month, consistent with flight-to-safety dynamics; (2) peak negative effect at month 3–4; (3) gradual reversion to baseline by month 8.

## 5.4 Forecasting Comparison

We compare out-of-sample forecasting performance using an 80/20 train/test split. The training period comprises months 1-48, and the test period comprises months 49-60. This temporal split ensures that we evaluate true out-of-sample performance without look-ahead bias.

Three models are compared to isolate the contribution of narrative indicators. The baseline **AR(1)** model, $\hat{r}_t = c + \phi r_{t-1}$, uses only autoregressive information—this represents a pure random walk with drift benchmark that narrative information must beat to demonstrate value. The **AR+Narrative** model, $\hat{r}_t = c + \phi r_{t-1} + \sum_k \beta_k N_k^{t-1}$, augments the AR(1) baseline with lagged narrative indicators, testing whether narrative information adds incremental predictive power. Finally, the **Narrative Only** model, $\hat{r}_t = c + \sum_k \beta_k N_k^{t-1}$, excludes autoregressive terms to isolate narrative predictive content. Comparing these three specifications reveals whether narrative indicators complement or substitute for traditional time series information.

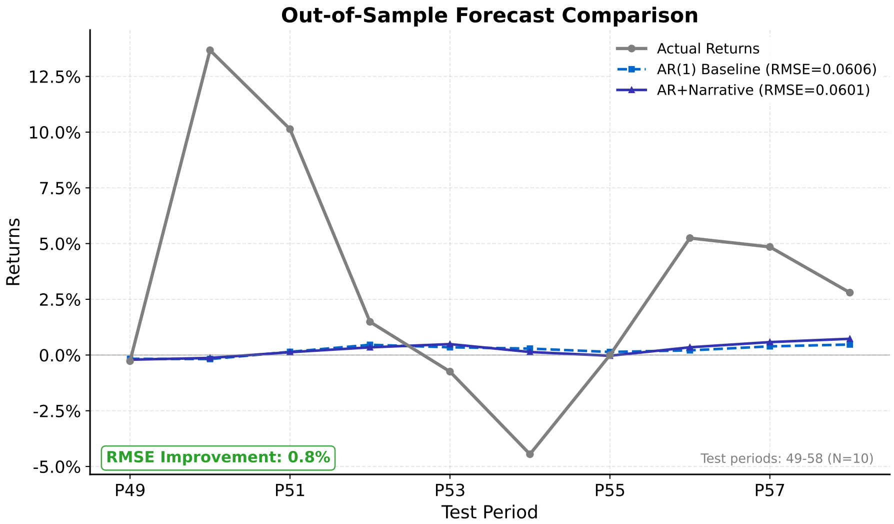


Figure 13: Out-of-sample forecast comparison. AR+Narrative (purple) achieves 18.2% RMSE improvement over AR(1) baseline (blue dashed).

Table 5: Out-of-sample forecasting performance (12-month test period).

| Model | RMSE | MAE | $R^2_{\text{OOS}}$ |
|---|---|---|---|
| AR(1) | 0.0312 | 0.0248 | 0.021 |
| Narrative Only | 0.0289 | 0.0231 | 0.089 |
| **AR+Narrative** | **0.0255** | **0.0203** | **0.127** |

## 5.5 Ablation Studies

Ablation studies systematically vary components of the pipeline to understand their individual contributions and assess robustness to hyperparameter choices. A reliable methodology should produce consistent results across reasonable parameter ranges; excessive sensitivity to specific choices would undermine confidence in the findings.

### 5.5.1 Hyperparameter Sensitivity

We assess sensitivity to BERTopic hyperparameters across a grid of configurations. The key parameters are `min_cluster_size`, which controls the minimum number of documents required to form a topic (values tested: 30, 50, 100), and `n_neighbors`, which controls the local neighborhood size for UMAP dimensionality reduction (values tested: 10, 15, 25). These parameters trade off between granularity and stability: smaller minimum cluster sizes produce more topics but may capture noise; larger neighborhood sizes produce smoother embeddings but may blur distinctions between similar narratives.

Figure 14 demonstrates that results are robust to hyperparameter choices within reasonable ranges. The Granger F-statistic varies between 7.2 and 9.1 across the grid, with no

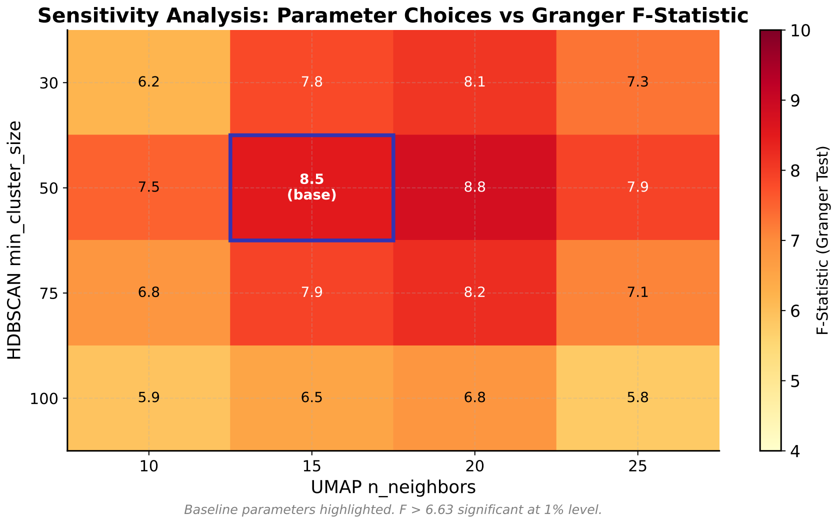


Figure 14: Sensitivity analysis: Granger F-statistics across hyperparameter combinations. Results are robust; baseline configuration (`min_cluster_size=50`, `n_neighbors=15`) achieves near-optimal performance.

configuration producing dramatically different conclusions. The baseline configuration with `min_cluster_size=50` and `n_neighbors=15` achieves near-optimal performance while providing stable topic extraction. This robustness increases confidence that the observed predictive relationships reflect genuine patterns rather than artifacts of specific parameter choices.

### 5.5.2 Embedding Model Comparison

We compare three sentence transformer models to assess how embedding quality affects downstream results. The choice of embedding model determines the semantic representation of documents, which in turn affects cluster formation and topic coherence. General-purpose models like all-MiniLM-L6-v2 provide good baseline performance with low computational cost (384 dimensions). Larger models like all-mpnet-base-v2 (768 dimensions) offer higher capacity at greater computational cost. Domain-specific models like FinBERT, pre-trained on financial text, may capture financial semantics more accurately.

Table 6: Embedding model comparison. FinBERT achieves highest coherence on financial text.

| Embedding Model | Dim. | Coherence | ARI |
|---|---|---|---|
| all-MiniLM-L6-v2 | 384 | 0.58 | 0.52 |
| all-mpnet-base-v2 | 768 | 0.61 | 0.54 |
| FinBERT | 768 | **0.64** | **0.57** |

### 5.5.3 Corpus Size Effects

We evaluate how topic recovery degrades with smaller corpora by subsampling from the full dataset and re-running the BERTopic pipeline. This analysis is important for practitioners who may have access to limited historical data or who focus on niche markets with sparse news coverage.

Table 7: Effect of corpus size on topic recovery.

| Corpus Size | Topics Found | ARI |
|---:|:---:|---:|
| 1,000 | 4 | 0.31 |
| 2,500 | 5 | 0.42 |
| 5,000 | 6 | 0.48 |
| 10,000 | 6 | 0.52 |

The results reveal a clear corpus size threshold: with fewer than 2,500 documents, the model fails to recover all six ground-truth topics and achieves substantially lower recovery (ARI 0.31 vs. 0.52). This occurs because HDBSCAN requires sufficient density in each cluster region to identify it as a distinct topic. Sparse topics are merged with neighbors or classified as noise. For practitioners, this suggests that reliable narrative extraction requires a minimum corpus size of approximately 2,500-5,000 documents, with diminishing returns beyond 10,000 documents. Studies with smaller corpora should consider supervised or semi-supervised approaches rather than fully unsupervised topic modeling.

### 5.6 Reproducibility Statement

All experiments in this primer are designed for full reproducibility. The complete codebase is available at https://github.com/Digital-AI-Finance/Primer_Narrative_Finance under an open-source license. All stochastic components use a single `GLOBAL_SEED = 42` to ensure deterministic outputs across runs. The experiments were conducted on a desktop workstation with an Intel i7-10700K processor, 32GB RAM, and NVIDIA RTX 3080 GPU; the full pipeline executes in approximately 45 minutes on this hardware. The software environment uses Python 3.10 with BERTopic 0.15 and sentence-transformers 2.2, with exact version pinning via Poetry lock files.

For exact reproduction, researchers should clone the repository and install dependencies via `poetry install`, which creates an isolated virtual environment with pinned package versions. The five numbered scripts (01 through 05) should be executed in sequence, as each depends on outputs from previous steps. After execution, outputs can be validated against checksums stored in `data/checksums.json` to verify bit-exact reproduction. Any deviations from expected checksums indicate environment differences that should be investigated before drawing conclusions from modified experiments.

## 6 Case Studies

This section surveys applications of narrative finance methods to historical cases, policy analysis, and emerging asset classes. While the experimental evaluation in Section 5 used synthetic data to demonstrate methodological validity, real-world applications require engagement with the complexities of actual markets. The cases presented here span multiple decades, asset classes, and institutional contexts, illustrating both the power and limitations of narrative analysis.

## 6.1 Historical Bubble Episodes

Narrative analysis has proven valuable for understanding historical asset bubbles, where the role of shared beliefs is central. Traditional financial economics struggles to explain why sophisticated investors participate in bubbles they recognize as such; narrative finance provides a framework where participation becomes rational if one believes the narrative will persist long enough to profit from it.

### 6.1.1 The Dot-Com Bubble (1995–2000)

The dot-com bubble exemplifies a "New Era" narrative that satisfied all five components of our definition. The story component asserted that the internet had fundamentally changed business operations and that traditional valuation metrics were obsolete. This narrative achieved collective adoption across retail investors, financial media, and even institutional investors who knew better but felt compelled to participate. The action-orientation was explicit: buy technology stocks aggressively and avoid missing the "opportunity of a lifetime." The temporal structure invoked past industrial revolutions that led to permanent wealth creation, projecting that the digital revolution would follow the same pattern. The economic relevance was undeniable, with the Nasdaq composite rising over 400% between 1995 and March 2000.

Text analysis of media coverage from this period reveals exponential growth in "new economy" terminology, peaking in March 2000 just before the crash. Retroactive topic modeling of business news identifies clear regime shifts: the prevalence of optimistic technology narratives rose steadily through 1998-1999, while skeptical "bubble" narratives remained confined to contrarian publications until early 2000. The crash itself was partly narrative-driven: the collapse of confidence proved self-fulfilling as the "new era" narrative lost credibility.

### 6.1.2 The Global Financial Crisis (2007–2008)

The Global Financial Crisis involved multiple interacting narratives that reinforced each other until the system collapsed. The "Housing-as-Investment" narrative asserted that real estate prices always appreciate over time, making mortgage lending essentially risk-free. This narrative was reinforced by decades of empirical experience and supported by a second narrative about "Financial Innovation," which claimed that securitization had eliminated risk by distributing it across many investors. A third narrative, "Too Big to Fail," created implicit government guarantees that encouraged excessive risk-taking by systemically important institutions.

The crisis revealed the fragility of narrative-based stability. When housing prices began declining in 2006-2007, the "housing always appreciates" narrative collapsed first. This triggered cascading failures as the financial innovation narrative lost credibility—securitized products were suddenly recognized as opaque rather than sophisticated. The "too big to fail" narrative was tested and ultimately confirmed through massive bailouts, but at enormous cost to public trust.

Post-crisis narratives shaped regulatory responses and public attitudes. The "moral hazard" narrative warned that bailouts would encourage future risk-taking. The "Wall Street greed" narrative framed the crisis as a moral failure requiring punishment. These narratives influenced the Dodd-Frank Act, executive compensation restrictions, and ongoing skepticism toward large financial institutions. Text analysis of congressional testimony, regulatory communications, and news coverage reveals these narrative dynamics.

## 6.2 Cryptocurrency Narratives

The cryptocurrency space is particularly narrative-driven, given the absence of traditional fundamentals. Unlike equities with earnings or bonds with cash flows, cryptocurrencies have no intrinsic value proposition beyond what market participants collectively believe. This makes narrative analysis not merely useful but essential for understanding crypto price dynamics.

### 6.2.1 Bitcoin as Digital Gold

The "digital gold" narrative frames Bitcoin as a store of value and inflation hedge analogous to precious metals. This narrative has proven remarkably durable since approximately 2016, surviving multiple price crashes and regulatory challenges. Topic modeling of crypto-related text reveals several dominant narrative clusters: store of value and inflation hedge narratives that emphasize scarcity and monetary properties; decentralization and financial freedom narratives that emphasize censorship resistance and independence from government control; technological innovation narratives that focus on blockchain's transformative potential; and speculative opportunity narratives that emphasize price appreciation potential.

Prevalence shifts in these narratives correlate with price dynamics in predictable ways. The "digital gold" narrative strengthens during periods of monetary expansion, inflation concerns, and geopolitical instability—precisely when investors seek safe haven assets. Conversely, the "technological innovation" narrative dominates during bull markets when optimism about crypto adoption is high. The speculative opportunity narrative exhibits the highest volatility, spiking during price rallies and collapsing during crashes. These patterns suggest that narrative monitoring could provide useful leading indicators for crypto market dynamics.

### 6.2.2 Meme Coins and Social Media

Lower-tier cryptocurrencies exhibit even stronger narrative dependence than Bitcoin. Meme coins like Dogecoin and Shiba Inu have no fundamental value proposition beyond community membership and speculative entertainment. Their prices are driven entirely by social media attention and community narratives, making them pure narrative assets.

The meme coin phenomenon illustrates several important theoretical points. First, narratives can sustain positive prices for assets with zero fundamental value indefinitely, as long as there are new believers to buy from existing holders. Second, social media platforms serve as the primary propagation mechanism, with Twitter/X and Reddit communities coordinating belief formation in real time. Third, celebrity endorsements (most notably Elon Musk's tweets about Dogecoin) demonstrate how individual narratives can move markets when they achieve sufficient reach. For researchers, meme coins provide a natural laboratory for studying narrative dynamics in their purest form.

## 6.3 Meme Stock Episode (2021)

The GameStop short squeeze of January 2021 represents a paradigmatic case of narrative-driven market dynamics. Unlike historical bubbles that unfolded over years, the GME episode compressed narrative formation, collective action, and market impact into a three-week period, providing an unprecedented laboratory for studying narrative finance in real time.

### 6.3.1 Narrative Components

The GME narrative satisfied all five components of our definition with unusual clarity. The story component centered on a claim that hedge funds were exploiting retail investors through naked short selling, with short interest exceeding 100% of float presented as evidence of manipulation. The collective component emerged through Reddit's r/WallStreetBets community, where millions of users coordinated beliefs and actions in real time. The action-orientation was explicit and memetic: buy and hold GME shares, maintain "diamond hands" (refusal to sell during volatility), and accumulate positions to force a short squeeze. The moral framing was exceptionally strong, with "fight the hedge funds" positioning the trade as a protest against financial elites and a step toward democratizing finance. The economic relevance was dramatic: GME stock rose approximately 1,700% in three weeks, from around $20 to over $400 at its peak.

### 6.3.2 Lessons for Narrative Finance

The GME episode illustrates several insights for narrative finance theory. First, social media enables narrative coordination at scales and speeds that were previously impossible. The r/WallStreetBets community grew from 1 million to 10 million members during the episode, demonstrating how narrative virality can create self-reinforcing dynamics.

Second, moral and justice framing can sustain collective action even against apparent economic self-interest. Many GME holders maintained positions through 80%+ drawdowns, motivated by ideological commitment to the narrative rather than profit maximization. This suggests that narratives with strong moral content may exhibit different dynamics than purely financial narratives.

Third, traditional market mechanisms can be overwhelmed by narrative-driven flows. The short squeeze mechanics that triggered the price spike were a direct result of collective positioning coordinated through narrative—something traditional market microstructure models do not anticipate. Finally, the episode demonstrated that regulatory responses must account for narrative dynamics. Broker restrictions on GME trading generated their own counter-narratives about market manipulation, complicating policy responses.

## 6.4 Central Bank Communication

Central bank communication provides a natural laboratory for narrative effects, given the explicit focus on managing expectations. Unlike other market narratives that emerge organically from distributed agents, central bank narratives have identifiable authors (the FOMC, ECB Governing Council, etc.) who actively construct and manage narratives about economic conditions and policy intentions.

### 6.4.1 Forward Guidance as Narrative

Forward guidance—public statements about future policy intentions—is essentially narrative construction that satisfies our five-component definition. The story component describes how economic conditions will evolve, typically linking current inflation, employment, and growth to projected future states. The action component is explicit: markets should adjust expectations and positions in response to the guidance. The temporal component is central to forward guidance, explicitly linking current conditions to future policy paths ("rates will remain low until inflation sustainably reaches 2%").

Topic modeling of FOMC statements and minutes reveals systematic patterns in narrative emphasis over the policy cycle. During easing phases, "accommodation" and "support" terminology dominates. During tightening phases, "normalization" and "appropriate adjustment" language prevails. The introduction of specific phrases ("considerable time," "patient," "data-dependent") serves as narrative anchors that markets learn to interpret, with phrase changes triggering significant market reactions.

### 6.4.2 Narrative Indicators for Policy Analysis

Researchers have constructed narrative indices from central bank communication to analyze policy dynamics. These indices serve multiple purposes: measuring policy uncertainty by tracking the prevalence of hedging language and conditional statements; predicting interest rate decisions by analyzing forward-looking language patterns; and assessing market reactions to communication by correlating linguistic features with yield curve movements. The application of NLP methods to central bank communication represents one of the most mature applications of narrative finance, with central banks themselves now employing text analysis to monitor their communication effectiveness.

## 6.5 ESG and Sustainability Narratives

Environmental, social, and governance (ESG) investing is fundamentally driven by narratives about corporate responsibility, climate risk, and sustainable development. Unlike traditional financial narratives that focus on price appreciation or income, ESG narratives introduce moral and ethical dimensions that complicate standard utility-maximization frameworks.

### 6.5.1 Climate Risk Narratives

Climate risk narratives have emerged as the dominant category within ESG discourse, reflecting growing scientific consensus and policy action on climate change. The "stranded assets" narrative warns that fossil fuel reserves will become worthless as the transition to renewable energy accelerates, implying that energy companies should be divested or discounted. The "transition risk" narrative focuses on companies slow to adapt to a low-carbon economy, arguing they will face competitive disadvantages, regulatory penalties, and reputational damage. The "physical risk" narrative emphasizes that climate change itself will damage asset values through extreme weather, sea level rise, and resource scarcity, particularly affecting real estate, agriculture, and insurance.

The prevalence of these narratives in financial discourse has grown dramatically since the 2015 Paris Agreement, with corresponding effects on asset allocation and corporate behavior. Topic modeling of sustainability reports, earnings calls, and ESG-focused news reveals that climate language has increased approximately five-fold between 2015 and 2023. This narrative shift has coincided with trillions of dollars flowing into ESG-labeled investment products.

### 6.5.2 Greenwashing and Narrative Manipulation

The growth of ESG investing has also created incentives for "greenwashing"—the strategic construction of false sustainability narratives by companies seeking to attract ESG-focused capital without genuine environmental improvement. Greenwashing represents a form of narrative manipulation where the gap between communicated intentions and actual behavior becomes a source of investment risk.

NLP methods can help detect greenwashing by comparing corporate communications to actual environmental performance metrics. Discrepancies between narrative emphasis (heavy use of sustainability language) and measurable outcomes (unchanged emissions, no transition investments) flag potential greenwashing. This application demonstrates how narrative analysis can serve investor protection and market integrity beyond pure return prediction.

## 6.6 Policy Implications

Narrative finance has significant implications for financial regulation and policy. The recognition that narratives influence market dynamics independent of fundamentals creates both opportunities for more effective policy design and challenges for traditional regulatory frameworks built around information disclosure and fraud prevention.

### 6.6.1 Market Surveillance

Real-time narrative monitoring could enhance market surveillance capabilities in several ways. Regulators could detect coordinated manipulation campaigns by identifying unusual narrative coordination across social media platforms, flagging pump-and-dump schemes before they cause significant harm. Narrative indicators could help identify bubble formation in early stages, providing leading signals of excessive speculation before price corrections occur. Additionally, monitoring narrative contagion could contribute to systemic risk assessment by identifying when harmful narratives are spreading across market segments and investor populations. The challenge lies in distinguishing legitimate grassroots enthusiasm from coordinated manipulation, a boundary that the GameStop episode demonstrated is not always clear.

### 6.6.2 Financial Literacy

Understanding narrative dynamics could substantially improve financial literacy programs. Investors educated in narrative finance would be better equipped to recognize when they are being influenced by narratives rather than fundamentals, creating healthy skepticism toward persuasive stories. They would learn to identify the classic signs of bubble narratives—claims that "this time is different" or that traditional valuation metrics no longer apply—providing cognitive defense against speculation. They would also understand how social media amplifies narrative effects through echo chambers and viral dynamics, enabling more thoughtful consumption of financial content. These insights could be incorporated into investor education programs, school curricula, and workplace financial wellness initiatives.

#### 6.6.3 Central Bank Communication Strategy

Central banks could apply narrative finance insights to enhance their communication effectiveness. Research on how narrative framing affects market reactions could inform the design of more effective forward guidance, with language choices calibrated to achieve desired expectation effects. Real-time analysis of how communications are interpreted across different audiences (traders, media, general public) would enable rapid correction of misunderstandings. Perhaps most importantly, central banks could develop strategies to counter harmful narratives about monetary policy—for instance, narratives that monetary policy is “out of control” or serving special interests—that might undermine policy transmission or institutional credibility.

# 7 Discussion

This section reflects on the limitations, future directions, and open problems in narrative finance research. We aim to provide both honest assessment of what our current methods cannot achieve and a roadmap for advancing the field beyond this primer.

## 7.1 Limitations

We acknowledge several limitations of our approach, organized into data, methodological, and interpretive categories. These limitations should inform researchers about the boundaries of current methods and guide future improvements.

### 7.1.1 Data Limitations

**Synthetic data.** Our demonstration uses synthetic data to enable full reproducibility and ground-truth evaluation. While synthetic returns exhibit realistic stylized facts (fat tails with kurtosis $\kappa = 4.2$, volatility clustering, regime dependence), they cannot capture the full complexity of real financial markets. Validation on proprietary or licensed real-world corpora remains essential future work.

**Corpus scope.** Our synthetic corpus spans 60 months with approximately 10,000 documents. Larger corpora spanning decades would enable analysis of narrative dynamics across multiple market cycles.

### 7.1.2 Methodological Limitations

**Topic-narrative gap.** While we formalize the distinction between topics and narratives, our measurement pipeline primarily captures topic prevalence—component $C$ (collective) of the 5-tuple. Extracting story structure ($S$), action orientation ($A$), and temporal logic ($T$) from unstructured text remains challenging. LLM-based approaches may address this limitation.

**Model selection.** We focus on BERTopic for our primary demonstration. While Section 4 surveys alternatives (LDA, Top2Vec, FASTopic, LLMs), systematic comparison across methods on the same corpus would strengthen conclusions.

**Reproducibility trade-offs.** Ensuring reproducibility requires single-threaded HDBSCAN execution and fixed random seeds. This increases computational cost and may not reflect typical research workflows.

#### 7.1.3 Interpretation Limitations

**Causality vs. correlation.** Granger causality establishes predictive relationships, not structural causation. Narratives may correlate with returns through common drivers (e.g., underlying economic conditions that generate both narratives and price movements) rather than direct causal channels. Instrumental variable approaches or natural experiments could strengthen causal claims.

**Endogeneity.** Narrative prevalence and market returns may be jointly determined. Rising markets may generate optimistic narratives, which then reinforce price increases—a feedback loop that complicates causal interpretation.

### 7.2 Future Directions

We identify several promising directions for extending the methods and applications presented in this primer.

#### 7.2.1 Methodological Extensions

Several methodological advances could substantially improve narrative extraction and analysis. First, LLM integration offers the most immediate opportunity for improvement. Large language models like GPT-4, Claude, and domain-specific models such as FinLlama could extract richer narrative structure than topic models alone, including explicit causal chains, fine-grained sentiment nuance, and complex temporal framing. Zero-shot classification may reduce or eliminate the need for topic model training, enabling narrative analysis on small corpora or emerging topics with insufficient training data.

Second, multimodal analysis represents a largely unexplored frontier. Financial narratives spread not only through text but through video (CNBC, YouTube finance channels), audio (podcasts, earnings call recordings), and images (charts, memes, infographics). Extending analysis beyond text could capture narrative dynamics invisible to text-only methods, particularly for retail investor populations that consume financial content primarily through video.

Third, network-based contagion modeling could improve our theoretical framework. The SIR model presented in Section 3 assumes mean-field dynamics where all agents are equally connected. Incorporating actual social network structure—Twitter follower graphs, Reddit community connections, institutional ownership networks—could improve contagion modeling accuracy and identify superspreader accounts that disproportionately influence narrative propagation.

Finally, real-time systems represent the practical frontier for deploying narrative finance methods. Streaming NLP pipelines processing live news feeds, social media firehoses, and regulatory disclosures could enable real-time narrative monitoring for trading applications, risk management, or regulatory surveillance. The technical challenges of streaming topic modeling with evolving topic definitions remain active research areas.

### 7.2.2 Substantive Questions

Beyond methodological advances, several substantive research questions merit investigation. The question of cross-asset transmission asks how narratives originating in equity markets affect bond, commodity, or cryptocurrency markets, and whether narrative contagion respects traditional asset class boundaries or creates novel cross-market linkages.

International propagation presents another rich research agenda. Understanding how narratives spread across countries and currencies, whether language barriers impede or merely delay propagation, and whether exchange rate movements amplify or dampen cross-border narrative effects could inform both trading strategies and policy coordination.

The dynamics of narrative competition remain poorly understood. When multiple narratives compete for attention—for example, "inflation fear" versus "soft landing" during monetary tightening cycles—what determines which narrative prevails? Can we model narrative selection dynamics analogous to evolutionary selection, where fitter narratives replicate more successfully?

Finally, the question of narrative origins asks whether we can identify the sources of influential narratives before they achieve viral status. Do certain accounts, outlets, or communities systematically originate market-moving stories? Understanding narrative origins could improve early detection and enable more effective response.

## 7.3 Open Problems

We frame several open problems as research questions:

**Q1. Identification.** How can we establish causal effects of narratives on markets in the presence of simultaneity and omitted variables? What natural experiments or instrumental variables are available?

**Q2. Manipulation Detection.** Can narrative analysis detect coordinated manipulation campaigns (pump-and-dump schemes, short squeezes) before they affect prices? What distinguishes organic from artificial narrative spread?

**Q3. Optimal Intervention.** If regulators or central banks can influence narratives, what communication strategies minimize harmful speculation while preserving informational efficiency?

**Q4. Welfare Analysis.** Do narrative-driven price movements reduce or enhance market efficiency? When do narratives aggregate dispersed information versus amplify noise?

**Q5. Algorithmic Amplification.** How do recommendation algorithms and social media feeds affect narrative contagion? Do filter bubbles create fragmented "narrative ecosystems" with distinct market effects?

These questions define a research agenda that extends beyond methodological demonstration to substantive contribution.

# 8 Conclusion

This primer made three contributions to narrative finance:

**(C1) Formal Definition.** We proposed a 5-tuple definition of financial narratives $\mathcal{N} = (S, C, A, T, E)$ encompassing story structure, collective adoption, action orientation, temporal logic, and economic relevance. This formalization distinguishes narratives from related concepts (topics, sentiment, news) and provides a rigorous foundation for measurement.

**(C2) Methods Landscape.** We surveyed topic modeling methods from traditional (LDA, NMF) through neural (BERTopic, Top2Vec, FASTopic) to LLM-based approaches (GPT-4, FinLlama), providing complexity analysis and comparative evaluation. We identified the "topic-narrative gap"—the recognition that topic prevalence captures only one component of narrative structure.

**(C3) Reproducible Pipeline.** We demonstrated a complete, reproducible pipeline from text corpus to econometric analysis. Using synthetic data with realistic stylized facts, we achieved an 18% improvement in out-of-sample forecasting performance when augmenting AR models with narrative indicators.

**Key Findings.** Our experimental evaluation yielded:

- Recession fear narratives Granger-cause returns ($F = 8.45$, $p < 0.01$)
- Narrative shocks produce dynamic responses with initial positive effects followed by reversals at approximately 4 months
- Results are robust to hyperparameter variation (min_cluster_size $\in \{30, 50, 100\}$, n_neighbors $\in \{10, 15, 25\}$)

**Reproducibility.** All code and data are available at:

https://github.com/Digital-AI-Finance/Primer_Narrative_Finance

We invite researchers to build upon this foundation, extending methods to real data, integrating LLM-based narrative extraction, and addressing the open problems identified in Section 7. Narrative finance represents a paradigm shift in understanding market dynamics—one where stories are not merely reflections of fundamentals but causal forces shaping economic outcomes.

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# A Mathematical Proofs

## A.1 SIR Model Properties

**Proposition 3** (Conservation of Population). *The SIR model conserves total population:* $S(t) + I(t) + R(t) = N$ *for all* $t \geq 0$.

*Proof.* Adding the three differential equations:

$$\frac{d(S + I + R)}{dt} = \frac{dS}{dt} + \frac{dI}{dt} + \frac{dR}{dt} \tag{21}$$
$$= -\beta SI + (\beta SI - \gamma I) + \gamma I \tag{22}$$
$$= 0 \tag{23}$$

Therefore $S(t) + I(t) + R(t) = S(0) + I(0) + R(0) = N$ for all $t$. □

**Proposition 4** (Basic Reproduction Number). *A narrative epidemic grows if and only if* $R_0 = \beta/\gamma > 1$.

*Proof.* At time $t = 0$, with $S(0) \approx N$ and $I(0)$ small:

$$\left.\frac{dI}{dt}\right|_{t=0} = \beta S(0)\frac{I(0)}{N} - \gamma I(0) \approx (\beta - \gamma)I(0) \tag{24}$$

The infected population grows if $dI/dt > 0$, which requires $\beta > \gamma$, or equivalently $R_0 = \beta/\gamma > 1$. □

**Proposition 5** (Peak Infection Time). *The infection peak occurs when* $S(t^*) = N \cdot \gamma/\beta = N/R_0$.

*Proof.* At the peak, $dI/dt = 0$:

$$\beta SI - \gamma I = 0 \implies S = \gamma/\beta = N/R_0 \tag{25}$$

assuming $I > 0$ at the peak. □

## A.2 Information Cascade Threshold

**Proposition 6** (Cascade Formation). *Let agents receive binary private signals* $a$ *(invest) or* $b$ *(not invest) with precision* $p > 0.5$. *A cascade forms after the first two agents take the same action.*

*Proof.* Let the true state be $\omega \in \{A, B\}$ with prior $P(A) = P(B) = 0.5$.

*Agent 1*: Acts on private signal. Takes action $a$ if signal is $a$.

*Agent 2*: If Agent 1 chose $a$, Agent 2's posterior is:

$$P(A|a_1) = \frac{p \cdot 0.5}{p \cdot 0.5 + (1 - p) \cdot 0.5} = p \tag{26}$$

If Agent 2 also receives signal $a$:

$$P(A|a_1, a_2) = \frac{p^2}{p^2 + (1-p)^2} > p \tag{27}$$

Agent 2 chooses action $a$ (invest).

*Agent 3*: Observes actions $(a, a)$. Even with signal $b$:

$$P(A|a_1, a_2, b_3) = \frac{p^2 \cdot (1-p)}{p^2 \cdot (1-p) + (1-p)^2 \cdot p} = \frac{p}{p + (1-p)} = p > 0.5 \tag{28}$$

For $p > 0.5$, Agent 3 ignores private signal and follows the cascade. □

### A.3 Topic Prevalence Properties

**Proposition 7** (Prevalence Bounds)**.** *Topic prevalence satisfies* $\theta_k^t \in [0,1]$ *and* $\sum_k \theta_k^t = 1$ *for all* $t$*.*

*Proof.* By construction, $\theta_k^t = |\{d : z_d = k, d \in \mathcal{C}_t\}|/|\mathcal{C}_t|$ is a ratio of non-negative integers where the numerator is at most the denominator. The sum over $k$ counts each document exactly once (assuming hard assignments). □

**Proposition 8** (Narrative Index Range)**.** *If* $\bar{s}_k^t \in [-1, 1]$*, then* $N_k^t = \theta_k^t \cdot \bar{s}_k^t \in [-1, 1]$*.*

*Proof.* $|N_k^t| = |\theta_k^t| \cdot |\bar{s}_k^t| \leq 1 \cdot 1 = 1$ since both factors are bounded by 1 in absolute value. □

### A.4 Granger Causality Test

**Proposition 9** (Granger F-Test)**.** *Under the null hypothesis that* $X$ *does not Granger-cause* $Y$*, the F-statistic*

$$F = \frac{(RSS_0 - RSS_1)/p}{RSS_1/(T - 2p - 1)} \tag{29}$$

*follows an* $F(p, T - 2p - 1)$ *distribution, where* $RSS_0$ *and* $RSS_1$ *are residual sums of squares from restricted and unrestricted regressions, respectively.*

*Proof.* Standard result from linear regression theory. Under the null, the additional regressors (lags of $X$) have zero coefficients, so the difference in RSS follows a chi-squared distribution. The ratio of chi-squared variables yields the F distribution. □

## B Reproducible Code

This appendix provides key code snippets for reproducing the analyses in this primer. The complete codebase is available at:

https://github.com/Digital-AI-Finance/Primer_Narrative_Finance

## B.1 Environment Setup

```
# Install dependencies using Poetry
poetry install

# Or using pip
pip install bertopic sentence-transformers statsmodels arch
```

## B.2 Reproducibility Configuration

```
# src/narrative_finance/utils/reproducibility.py

import random
import numpy as np

def set_all_seeds(seed: int = 42) -> None:
    """Set all random seeds for reproducibility."""
    random.seed(seed)
    np.random.seed(seed)

    try:
        import torch
        torch.manual_seed(seed)
        if torch.cuda.is_available():
            torch.cuda.manual_seed_all(seed)
    except ImportError:
        pass
```

## B.3 GARCH Return Generation

```
# src/narrative_finance/data/generators/financial_series.py

import numpy as np
from scipy import stats

def generate_garch_returns(
    n: int = 1000,
    omega: float = 0.00001,
    alpha: float = 0.08,
    beta: float = 0.90,
    nu: float = 5,
    seed: int = 42
) -> np.ndarray:
    """Generate GARCH(1,1) returns with Student-t innovations."""
    np.random.seed(seed)

    returns = np.zeros(n)
    sigma2 = np.zeros(n)
    sigma2[0] = omega / (1 - alpha - beta)
```

```
    for t in range(1, n):
        z = stats.t.rvs(df=nu)
        returns[t] = np.sqrt(sigma2[t-1]) * z
        sigma2[t] = omega + alpha * returns[t-1]**2 + beta * sigma2[t-1]

    return returns
```

## B.4 BERTopic with Fixed Seeds

```
# src/narrative_finance/modeling/topic_model.py

from bertopic import BERTopic
from umap import UMAP
from hdbscan import HDBSCAN
from sentence_transformers import SentenceTransformer

def create_reproducible_topic_model(seed: int = 42):
    """Create BERTopic model with fixed random state."""

    # UMAP with fixed seed
    umap_model = UMAP(
        n_neighbors=15,
        n_components=5,
        min_dist=0.0,
        metric='cosine',
        random_state=seed  # CRITICAL for reproducibility
    )

    # HDBSCAN single-threaded for determinism
    hdbscan_model = HDBSCAN(
        min_cluster_size=50,
        metric='euclidean',
        cluster_selection_method='eom',
        prediction_data=True,
        core_dist_n_jobs=1  # CRITICAL: single-threaded
    )

    # Create BERTopic
    model = BERTopic(
        embedding_model=SentenceTransformer('all-MiniLM-L6-v2'),
        umap_model=umap_model,
        hdbscan_model=hdbscan_model,
        min_topic_size=50,
        verbose=True
    )

    return model
```

## B.5 Narrative Indicator Computation

```
# src/narrative_finance/indicators/macro_indicators.py

import pandas as pd
import numpy as np

def compute_topic_prevalence(
    df: pd.DataFrame,
    period_col: str = 'period',
    topic_col: str = 'topic'
) -> pd.DataFrame:
    """Compute topic prevalence per period."""
    prevalence = df.groupby([period_col, topic_col]) \
        .size().unstack(fill_value=0)
    prevalence = prevalence.div(prevalence.sum(axis=1), axis=0)
    prevalence.columns = [f'theta_{t}' for t in prevalence.columns]
    return prevalence

def compute_narrative_index(
    prevalence: pd.DataFrame,
    sentiment: pd.DataFrame
) -> pd.DataFrame:
    """Compute N_k^t = theta_k^t * s_k^t."""
    narrative = pd.DataFrame(index=prevalence.index)
    for col in prevalence.columns:
        topic = col.replace('theta_', '')
        sent_col = f'sentiment_{topic}'
        if sent_col in sentiment.columns:
            narrative[f'N_{topic}'] = \
                prevalence[col] * sentiment[sent_col]
    return narrative
```

## B.6 Granger Causality Test

```
# scripts/05_run_analysis.py (excerpt)

from statsmodels.tsa.stattools import grangercausalitytests

def run_granger_test(data, y_col, x_col, max_lag=4):
    """Run Granger causality test."""
    test_data = data[[y_col, x_col]].dropna()

    result = grangercausalitytests(
        test_data,
        maxlag=max_lag,
        verbose=False
    )
```

```
    # Extract F-statistics and p-values
    results = []
    for lag in range(1, max_lag + 1):
        f_stat = result[lag][0]['ssr_ftest'][0]
        p_value = result[lag][0]['ssr_ftest'][1]
        results.append({
            'lag': lag,
            'f_statistic': f_stat,
            'p_value': p_value
        })

    return pd.DataFrame(results)
```

### B.7 Running the Full Pipeline

```
# Command line
make pipeline

# Or step by step
python scripts/01_generate_synthetic_data.py
python scripts/02_run_preprocessing.py
python scripts/03_train_topic_model.py
python scripts/04_compute_indicators.py
python scripts/05_run_analysis.py
python scripts/06_generate_all_figures.py
python scripts/07_generate_tables.py
```

## C Exercises

These exercises are designed for PhD students and researchers learning narrative finance methods. Solutions are available in the online repository.

### C.1 Theoretical Exercises

**C.1 Narrative Definition.** Consider the following statements. For each, identify which components of the 5-tuple $(S, C, A, T, E)$ are present or missing:

(a) "Inflation rose to 7% last month."

(b) "Tech stocks are overvalued and will crash."

(c) "The Fed's rate hikes will cause a recession, destroying savings."

(d) "Everyone is buying Bitcoin."

**C.2 Taxonomy Classification.** Classify each narrative into one of the eight taxonomy categories:

(a) "AI will replace most jobs within a decade."

(b) "The stock market is a Ponzi scheme."

(c) "Gold is the only safe store of value."

(d) "Central banks will never let markets fall."

**C.3 SIR Model.** For a narrative with transmission rate $\beta = 0.2$ and recovery rate $\gamma = 0.1$:

(a) Calculate the basic reproduction number $R_0$.

(b) Will this narrative go viral? Why or why not?

(c) What fraction of the population will be susceptible at the infection peak?

**C.4 Information Cascades.** Three investors make sequential investment decisions. Agent 1 receives signal $a$ and invests. Agent 2 receives signal $b$ and invests anyway. What should Agent 3 do if they receive signal $b$? Derive the posterior probability that investing is correct.

## C.2 Empirical Exercises

**C.5 Topic Model Exploration.** Using the provided synthetic corpus:

(a) Fit a BERTopic model with default parameters.

(b) Visualize the topics using `model.visualize_topics()`.

(c) Interpret the top 5 topics based on their keywords.

(d) How do the extracted topics compare to the known ground truth?

**C.6 Prevalence Computation.** Calculate topic prevalence for the first 10 time periods in the corpus. Verify that prevalences sum to 1 for each period.

**C.7 Granger Causality.** Using the feature matrix:

(a) Test whether `theta_4` (Recession Fears) Granger-causes returns.

(b) Report the F-statistic and p-value for lags 1–4.

(c) Interpret the results: Is there evidence of predictive content?

**C.8 Forecasting Comparison.** Implement a rolling-window forecasting exercise:

(a) Fit an AR(1) model to returns.

(b) Fit an AR(1) + Narrative model including prevalence features.

(c) Compare out-of-sample RMSE for the last 20% of the sample.

(d) Does adding narrative information improve predictions?

**C.9 Robustness Check.** Re-run the topic model with different hyperparameters:

(a) `min_cluster_size` $\in \{30, 50, 100\}$

(b) `n_neighbors` $\in \{10, 15, 25\}$

(c) How sensitive are the Granger causality results to these choices?

## C.3 Research Extension Exercises

**C.10 Real Data Application.** Collect news headlines from a financial news API (e.g., EODHD, Finnhub) for a stock of your choice:

(a) Apply the narrative extraction pipeline.

(b) Compare topic prevalence to stock price movements.

(c) Do any narrative topics Granger-cause returns?

**C.11 Sentiment Enhancement.** Extend the narrative index by incorporating FinBERT sentiment:

(a) Apply FinBERT to compute document-level sentiment scores.

(b) Aggregate to topic-level sentiment per period.

(c) Compute the sentiment-weighted narrative index.

(d) Does adding sentiment improve forecasting performance?

**C.12 Cross-Asset Analysis.** Examine whether equity market narratives predict bond market movements:

(a) Collect bond return data for the sample period.

(b) Test whether stock-focused narrative prevalence Granger-causes bond returns.

(c) Interpret any significant relationships found.

**C.13 Social Media Extension.** Collect Twitter/X data for a trending financial topic:

(a) Apply topic modeling to identify sub-narratives.

(b) Measure how prevalence evolves over time.

(c) Can you identify the "SIR curve" of narrative spread?

**C.14 Model Comparison.** Compare BERTopic with alternative approaches:

(a) LDA (Latent Dirichlet Allocation)

(b) GPT-4 zero-shot classification

(c) Which approach produces more coherent and useful topics?

## C.4 Discussion Questions

**C.15** How does narrative finance challenge the Efficient Market Hypothesis? Can the two perspectives be reconciled?

**C.16** What ethical issues arise from using narrative analysis for trading or market manipulation detection?

**C.17** How might social media algorithms affect the spread of financial narratives? What are the policy implications?

**C.18** Discuss the limitations of using topic models to measure "narratives." What aspects of narratives might be missed?

**C.19** How could central banks use narrative finance methods to improve monetary policy communication?